TripEnergy

Estimating Personal Vehicle Energy Consumption Given Limited Travel Survey Data

James McNerney, Zachary A. Needell, Michael T. Chang, Marco Miotti, and Jessika E. Trancik

Estimating personal vehicle energy consumption is important for nationwide climate policy, local and statewide environmental policy, and technology planning. Transportation energy use is complex, depending on vehicle performance and the driving behavior of individuals, as well as on travel patterns of cities and regions. Previous studies combine large samples of travel behavior with fixed estimates of per mile fuel economy or use detailed models of vehicles with limited samples of travel behavior. This paper presents a model for estimating privately operated vehicle energy consumption—TripEnergy—that accurately reconstructs detailed driving behavior across the United States and simulates vehicle performance for different driving conditions. The accuracy of this reconstruction was tested by using out-of-sample predictions, and the vehicle model was tested against microsimulation. TripEnergy consists of a demand model, linking GPS drive cycles to travel survey trips, and a vehicle model, efficiently simulating energy consumption across different types of driving. Because of its ability to link small-scale variation in vehicle technology and driver behavior with large-scale variation in travel patterns, it is expected to be useful for a variety of applications, including technology assessment, cost and energy savings from ecodriving, and the integration of electric vehicle technologies into the grid.

Personal vehicles in the United States consumed an estimated 1.7×10^{19} J of secondary energy in 2014 (*1*) during more than 200 billion trips (*2*). This demand arose from travelers using diverse transportation technologies and travel patterns. Quantifying this energy consumption and its environmental effects at the scale of countries, regions, and cities—and relating those aggregates to microscale determinants—is critical for developing sustainable transportation strategies.

A variety of methods exists to estimate the energy use of trips. Top-down methods such as energy sales accounting provide data on large-scale environmental effects but not the low-level determinants needed to evaluate, for example, the effects of future technological changes on total energy use. Bottom-up methods such as dynamometer testing and microsimulation provide high-fidelity representations of vehicle performance and driver behavior, but they rely on data that are not available at the macroscale needed to understand the societal impacts of policies.

Institute for Data, Systems, and Society, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139. Corresponding author: J. E. Trancik, trancik@mit.edu.

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Connecting energy-related impacts, such as greenhouse emissions, to low-level factors is similarly important. Privately operated vehicles (POVs) are one of the primary emitters of greenhouse gases in the United States, and reducing the carbon intensity of transportation is a major component of mitigation scenarios (*3, 4*). Future emissions will be affected by current policies such as fuel economy standards (*5*), technology developments such as battery electric vehicles (*6*), and demographic changes such as urbanization (*7*). Evaluating how plausible emissions targets are means connecting them to technology, infrastructure, or behavior changes needed to meet these goals.

Presented here is a method for estimating POV energy consumption that is designed for this wide range of uses. The TripEnergy method estimates energy aggregates consistent with top-down inventories (e.g., total gasoline consumption) but computes them from the bottom up using second-by-second reconstructions of driving patterns across the United States and an energy model that works with specific, existing vehicles. As a result, TripEnergy can model the effects on aggregate energy use from changes to vehicle technology and driving behavior. TripEnergy can estimate energy requirements for individual trips for a wide variety of vehicles, and it can operate probabilistically, producing a distribution of possible energies for each trip. Energy requirements can be flexibly aggregated by region, trip purpose, vehicle type, and a large number of socioeconomic variables. These abilities allow more coverage than models based only on GPS surveys or direct vehicle modeling, but they can address a wider range of questions than possible with fleetwide emissions models.

BACKGROUND

A summary is given of some widely used methods for estimating POV energy consumption. TripEnergy does not replace these methods but adds new capabilities.

Bottom-Up Methods

Bottom-up methods give energy consumption for individual trips based on direct measurement or simulation. Many studies rely on published measurements of energy consumption per distance to translate miles of travel into estimates of energy or emissions. In the United States, EPA requires fuel economy labeling of all new personal vehicles, measured in mpg or mpg-equivalent (mpge) for electric vehicles. These estimates are derived from dynamometer tests (*8*), where a vehicle is driven through standardized drive cycles (*9*), and have been used, for example, to study range requirements in electric vehicles using GPS data (*10, 11*) or to estimate the fuel price elasticity of energy use (*12*).

To capture greater variation in operating conditions than in EPA drive cycles, some researchers have supplemented EPA results with direct energy readings from a vehicle's onboard computer (*13, 14*). Microsimulation of vehicles has also been used to capture variation in operating conditions (*15, 16*). One use of these simulations has been to capture energy consumption during the use phase of life-cycle assessments (*17*), allowing the effects of typical driving conditions on life-cycle impacts to be studied.

While widely useful, these methods are not suitable for all research questions. Methods using a single fuel economy estimate cannot capture variations in energy use with driving style (*18*) or climate (*19*), introducing biases for, as examples, congested city driving or moderate speed highway driving, conditions likely to have particularly high or low energy intensity (*17, 20, 21*). Dynamometer testing and onboard measurement can provide data for these extreme conditions, but data collection is impractical for large numbers of trips and vehicle types.

Top-Down Methods

Top-down methods can provide accurate assessments of energy consumption in aggregate. These methods use data on energy sales and trace backward to when and how energy was used for transportation. In the United States, for example, FHWA collects data on statewide and national gasoline consumption from gas tax receipts, converting barrels of oil to energy use and CO_2 emissions (*22*). For well-mixed greenhouse gases, this approach is often deemed accurate enough for modeling and inventory purposes. Top-down accounting is also used to extrapolate future trends in gasoline consumption from fleet-average fuel economy and vehicle miles traveled (*23*), and to construct localized emissions inventories. For example, Gately et al. use roadway-level travel volumes to create a high-resolution spatial inventory of U.S. transportation-related greenhouse emissions (*24*).

For evaluating vehicle technologies, however, top-down inventories lack critical details, such as the effects of driving conditions on vehicle performance (*25*). Inventories lack detail needed to address some policy questions related to meeting users' technology needs, charging infrastructure, and the impacts of electric vehicle charging on the electric grid.

Hybrid Methods

Combining large, representative sample sizes with realistic trip patterns has been an ongoing goal of transportation modeling. Some methods accomplish this by using the output of travel demand models as proxies for real-world data. They include four-step network flow models and more complex activity-based or car-following models. Simulated trips can be fed into software such as MOVES (*26*) and combined with information on expected fleet composition, weather, and other variables to estimate energy and emissions for cities or regions. MOVES calculates the expected emissions intensity of a given vehicle mile of travel using distributions of energy intensity for different road types and travel speeds, resulting in energy consumption estimates for particular roadways (*27*). Others generate synthetic drive cycles from travel demand models and combine them with vehicle simulation (*21, 28*) or directly link microscopic travel demand simulations with detailed vehicle models (*29*).

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

MODEL REQUIREMENTS AND APPLICATIONS

TripEnergy aims to meet two general requirements. First, it produces accurate energy estimates, for a wide range of vehicles, when applied to realistic driving behavior. Second, it produces estimates for individual trips, national aggregates, and various levels of aggregation in between. Energy requirements vary greatly from trip to trip owing to variations in vehicle technology, driving style (*18*), and ambient temperature (*19*). Accounting for these variations lets fuel economy vary realistically with trip characteristics, enabling applications that require energy estimates resolved by location, time, or trip. Additionally, because trip-by-trip energy consumption is highly variable, this method should produce a probabilistic picture of energy intensity, which is often more relevant to users' needs.

The most accurate estimate of an individual POV trip's energy consumption is likely to come from microsimulation or onboard instrumentation, while the best measure of national energy use comes from accounting of fuel sales. The method presented should bridge these data types to allow analyses that run across scales, that is, involving both small-scale technology performance and large-scale energy demand. An example would be a comparison of the fuel economy and energy use of suburban residents with those in the inner core of a city.

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

The TripEnergy model presented meets these needs while addressing the limitations in data. It combines data from the National Household Travel Survey (NHTS) (*2*); several GPS-based travel surveys (*31–33*); EPA emissions test parameters and results (*8, 34*); and historical weather data (*35*). TripEnergy can model a wide range of vehicles because it draws on widely available EPA vehicle test results, unlike many microscopic emissions simulators that rely on extensive data collection from a few vehicles. TripEnergy consists of a vehicle model, designed to capture variations in POV performance under a range of driving conditions, and a demand model, designed to reproduce travel patterns across the United States at high resolution.

MODEL

The demand model pairs trips from a travel survey with plausible second-by-second drive cycles and external temperature. The vehicle model computes energy use given a drive cycle, ambient temperature, and a specified vehicle type (Figure 1). These components separate the factors influencing energy consumption into two groups—vehicle characteristics such as mass, drag coefficients, and powertrain efficiency; and trip characteristics, particularly speed and weather conditions. Treating these factors as independent is a minor simplification that lets one supplement broad survey data with detailed descriptions of trips needed to estimate energy use.

In Figure 1, the demand model combines low-resolution data (*2*) 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 dynamometer test results from EPA, converts this information into an estimate for a trip's energy consumption.

Demand Model

The demand model begins with a user selecting a population of trips for study from the NHTS (*2*). The NHTS is the most comprehensive source of data on travel behavior in the United States, compiled by FHWA about once every 10 years. The 2009 survey covers about 1 million personal vehicle trips in the United States, using a weighting scheme to ensure that results are demographically and geographically representative. The NHTS provides a wide variety of data on individual trips, including region, number of passengers, trip purpose, and many socioeconomic variables. By using these variables, many different subsets of trips can be isolated for analysis depending on the application.

Trip distances and times from the NHTS are self-reported, and travel surveys have shown evidence of rounding and other reporting errors (*36*). To correct for rounding, a model of traveler rounding was fit to the NHTS trip distance and time distributions, providing the probability $p(x|\tilde{x})$ that a rounded distance or time $\tilde{x}$ was originally x. As described in Needell et al., this function can then be used to estimate the distribution of the original unrounded distances and times (*37*).

The purpose of the demand model is to augment the data in the NHTS with detailed information needed to estimate a range of energy values that an observed trip could have had. In the drive-cycle matching component, each trip is linked with a set of similar GPS drive cycles. The drive-cycle matching draws from a GPS database with ~112,000 drive cycles collected over several regional travel studies (*31–33*). Similar GPS trips are defined as ones that fall within a set window around the original trip in distance and duration. This procedure was found to sufficiently differentiate between different types of trips with different energy requirements, as illustrated in Figure 2.

In Figure 2, the right column shows two drive cycles corresponding to 8-mi trips, with durations of 10 min (Figure 2*b*) and 22 min (Figure 2*d*). The left column (Figure 2, *a* and *c*) shows the distribution of fuel economy values for trips with similar distance and duration as chosen by the demand model. (Ambient temperature is held fixed.) 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.

Trips are also linked with a range of external temperatures. Using an approach similar to that of Yuksel and Michalek (*14*), each NHTS trip is paired with a weather station in the typical meteorological year database based on its reported location (its core based statistical area if one is reported; otherwise its state). A range of possible temperatures is chosen from the database according to the reported month and time-of-day of the trip.

The linked drive cycle and temperature give plausible operating conditions of the POV trip observed in the NHTS. Each combination of drive cycle, temperature, and derounding can be fed into the vehicle model described as follows, leading to a probability distribution for energy requirements of each NHTS trip.

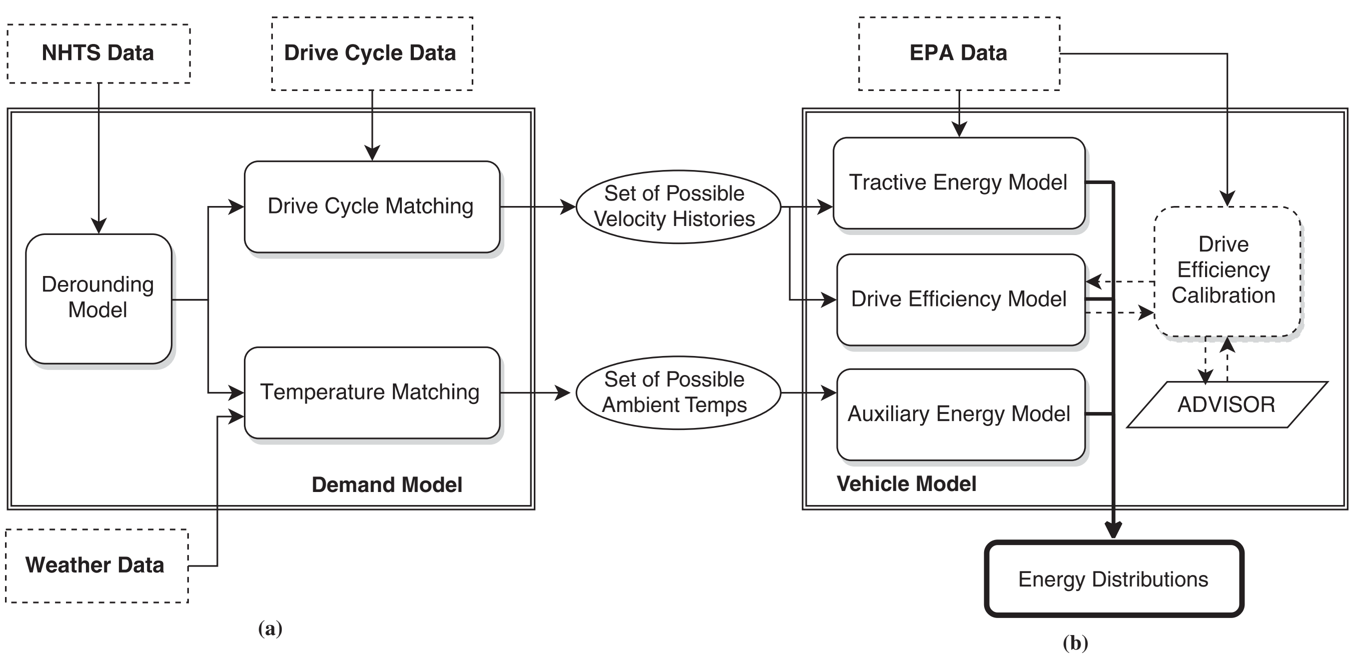

FIGURE 1 TripEnergy model diagram, showing (*a*) demand model and (*b*) vehicle model.

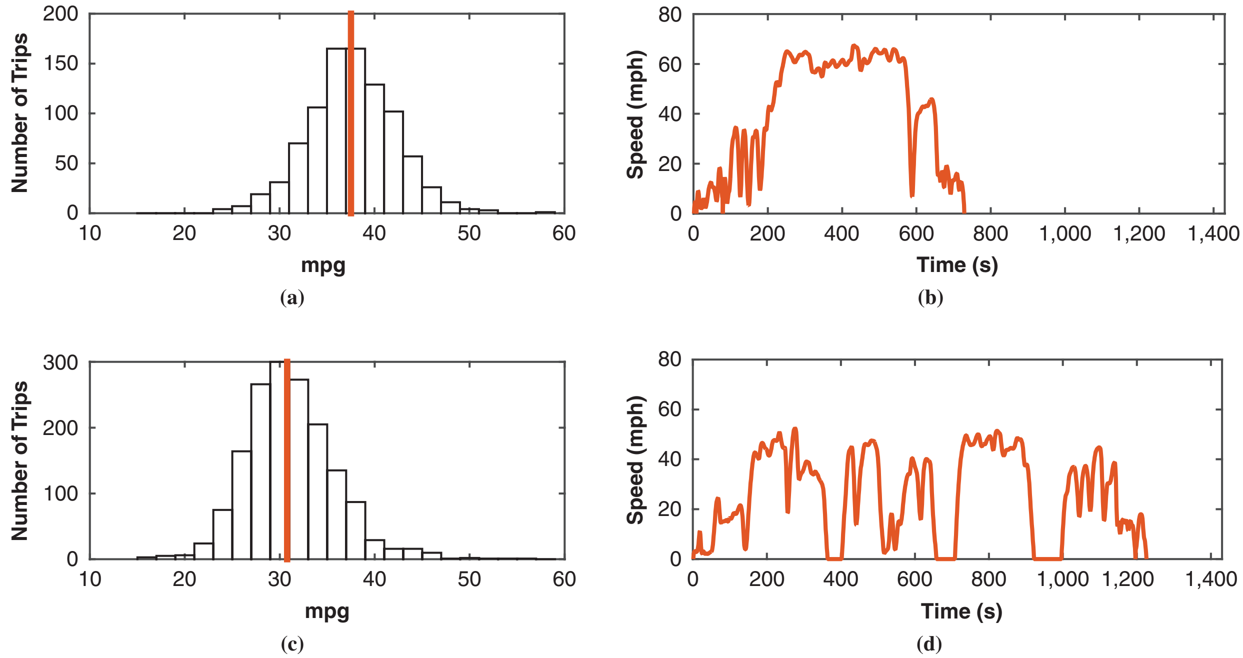

FIGURE 2 Example of effect of trip speed on fuel economy of 2014 Ford Focus: orange vertical line indicates median fuel economy in (*a*) and (*c*).

Vehicle Model

For convenience, TripEnergy decomposes a trip's total energy use E_{use} into drive energy E_{drive} needed for vehicle motion and auxiliary energy used for other purposes, mainly climate control. Thus, one has $E_{\text{use}} = E_{\text{drive}} + E_{\text{aux}}$. To compute E_{drive}, it is factored into final energy ε_{tr}, also known as tractive energy, delivered to the wheels and a drive efficiency factor η_{drive}:

$$E_{\text{drive}} = \frac{\varepsilon_{\text{tr}}}{\eta_{\text{drive}}} \tag{1}$$

(Preconversion energies, measured at the battery or gas tank, are written in script and final energies delivered to wheels and auxiliary systems in normal font.)

A trip's tractive energy can be computed from drive cycles received from the demand model using standard models of vehicle motion. Tractive power output of a vehicle is a function of its speed and acceleration:

$$P_{\text{tr}}(v) = av + bv^2 + cv^3 + (1+\varepsilon)\text{m}v\frac{dv}{dt} \tag{2}$$

The coefficients a, b, and c are dynamometer or coastdown coefficients published by EPA for many vehicles (*34*), m is vehicle mass, and ε is a factor accounting for the rotational inertia of a vehicle, assumed to be 1.05 here. Positive values of P_{tr} (corresponding to energy being drawn by the engine) can be integrated over a drive cycle to compute tractive energy ε_{tr} for the trip. The surveys lack data on elevation changes during a trip from which to compute potential energy changes. The highlighted applications require estimates of the daily energy consumption of individual vehicles, or aggregate energy for a fleet of vehicles, for which the effects of trip elevation changes will cancel out.

Conversion losses are significant for all POVs. An internal combustion engine vehicle (ICEV), for example, is thermodynamically limited to efficiencies η_{drive} typically less than 0.4. The nonlinear relationship between engine operating conditions and fuel consumption can be modeled analytically (*38*). Rakha et al. (*39*) present a related method using fuel economy test result data to fit this function, as does Lutsey (*40*). The approach here is similar, exploiting EPA corporate average fuel economy (CAFE) test results. A trip's total energy consumption ΔE_B and tractive energy consumption ε_{tr} can be calculated from reported unadjusted fuel economies, the CAFE drive cycles, and a vehicle's dynamometer coefficients. Using the formulation for total energy previously described, η_{drive} can then be calculated for a particular CAFE drive cycle as

$$\eta_{\text{drive}} = \frac{\varepsilon_{\text{tr}}}{\Delta E_B - \dfrac{\varepsilon_{\text{aux}}}{\eta_{\text{aux}}}} \tag{3}$$

Using the CAFE city and highway drive cycles, estimates are made of two values of η_{drive}. Since η_{drive} varies with driving behavior, a two-parameter function for η_{drive} is used based on the drive cycle that is calibrated to reproduce energy use for the two CAFE drive cycles. The form of this function is used on the basis of physical intuition and modeling in the vehicle simulator ADVISOR [described in more detail in Needell et al. (*37*)]. But it follows the intuition that internal combustion engines are more efficient at higher power, while battery electric vehicle (BEV) powertrain and regenerative braking efficiencies are roughly constant over a wide range of speed and torque.

Preconversion auxiliary energy is factored into final auxiliary energy delivered to auxiliary systems and the auxiliary efficiency: $E_{\text{aux}} = \varepsilon_{\text{aux}}/\eta_{\text{aux}}$. In typical driving, most auxiliary energy use comes from climate control (*41*). The external temperature received from the demand model determines how hard climate controls must work to maintain cabin temperature within a comfortable range. Heating, ventilation, and air conditioning (HVAC) energy consumption is modeled with a steady-state heat balance model: $P_{\text{thermal}} = k|\Delta T|$, with the thermal constant k taken to be 350 W/C°. HVAC power depends on the thermal load to maintain cabin temperature and the coefficient of performance of the climate control system used (e.g., a heat pump, radiant heater, or air conditioner). A constant power of 250 W is added to power other auxiliaries such as dashboard lights and power steering (*42*). The efficiency η_{aux} is taken to be a constant for each powertrain type [equal to 0.185 for ICEVs and 0.81 for BEVs, which take into account typical powertrain efficiency and power conversion losses; see Needell (*37*), supplementary information].

MODEL VALIDATION

Overall Fuel Economy Without Adjustment Factors

EPA fuel economy estimates (*8*) are derived by multiplying raw, unadjusted values measured during CAFE tests by adjustment factors (*9*), which bring fuel economy into better agreement with values experienced in real-world driving (*18*) (Table 1). The need for these artificial adjustment factors, which can be on the order of 30%, is thought to arise from differences between the drive cycles used in the tests and real-world drive cycles. By using a realistic population of drive cycles to account for real-world driving, the method here produces estimates close to (within 5% to 11% for the vehicles shown here) adjusted fuel economies without the need for adjustment factors. The model has been calibrated on two ICEVs and two BEVs and shows similar values to what EPA estimates after making adjustments.

Reproducing BEV and ICEV Performance Behavior

BEVs and hybrid electric vehicles tend to perform best in urban driving, where low-speed, start-and-stop driving predominates and regenerative braking can salvage the most energy possible. Conventional ICEVs perform best during moderate-speed highway driving, where powertrain efficiency is high and energy losses from braking are minimized (*17*). The model here reproduces these performance patterns (Figure 3). A strong dependence is seen on average speed in agreement with expected performance for both vehicle types. A secondary dependence is seen on trip distance where, for a given average speed, fuel economy tends to increase with trip distance for an ICEV but decreases for a BEV. This occurs because longer-distance trips tend to include more highway driving.

In Figure 3, the top plots are for the 2014 Ford Focus (an ICEV), and bottom plots are for the Nissan Leaf (a BEV). The left column shows average fuel economy, in units of mpg for the Focus (Figure 3*a*) and mpge for the Leaf (Figure 3*c*), for trips in a given distance and average speed bin. The right column shows the variability in fuel economy within a bin, measured by the coefficient of variation (CV) of fuel economy (the standard deviation divided by the average). The ICEV realizes its highest fuel economy for moderately high-speed, long-distance trips. The BEV realizes its highest fuel economy for moderately slow, short trips.

One can also study variability in fuel economy given the distance of a trip. Variability in fuel economy is not easily probed by other methods yet is important because it makes vehicle range uncertain. Fuel economy is most variable for short trips in ICEVs and slow trips in BEVs. In another paper, the researchers exploit this capability of TripEnergy to evaluate the way BEV range differs for rural and urban drivers (*37*).

Single-Trip Energy and Aggregate Energy Estimation

A cross-validation test was performed in which 2,000 GPS trips were used to simulate survey data. The energies of these trips were computed using the vehicle simulator ADVISOR (*16*), and these values were accepted as ground truth. The accuracy of three methods was compared for estimating these energies using only the trip distance and time that would be known if these trips came from survey data. The first method assumes all trips have EPA's estimated overall fuel economy. The second method, labeled the average mpg method, equates the fuel economy with the average of the survey trips. This method represents the best possible fixed fuel economy method for this sample of trips. The third method is TripEnergy, which uses the distances and times of the survey trips. In addition, energy estimates were produced using just the vehicle model of TripEnergy. Here the full drive cycles of the survey trips are passed into the vehicle model. This method would not be applicable to survey data, but including it helps distinguish error from the vehicle model and error from drive cycle matching.

TABLE 1 Comparison of Fuel Economies Estimated by EPA and TripEnergy

	2011 Ford Explorer		2013 Nissan Leaf		2014 Tesla Model S		2014 Ford Focus	
Fuel Economy	EPA Estimate	TripEnergy Estimate	EPA Estimate	TripEnergy Estimate	EPA Estimate	TripEnergy Estimate	EPA Estimate	TripEnergy Estimate
Highway (unadjusted)	34.7	34.7	146.4	146.4	121.5	121.5	50.4	50.4
City (unadjusted)	21.9	21.9	184.2	184.2	118.6	118.6	33.5	33.5
Overall (unadjusted)	27.7	na	167.2	na	119.9	na	41.1	na
EPA adjustment factor	0.72	na	0.69	na	0.79	na	0.73	na
Overall (adjusted)	20	22.2	116	109.7	95	85.7	30	31.8

NOTE: na = not applicable. EPA highway and city fuel economies are measured, unadjusted values, while the overall (unadjusted) fuel economy is a weighted average of the two (weights: 0.45 highway; 0.55 city). The unadjusted fuel economies are modified by adjustment factors to an overall, adjusted estimate of fuel economy. TripEnergy highway and city fuel economies are based on the EPA city and highway drive cycles. The efficiency component of the model is calibrated to match the city and highway fuel economies, and overall fuel economy is then based on an average over all privately operated vehicle trips in the National Household Travel Survey.

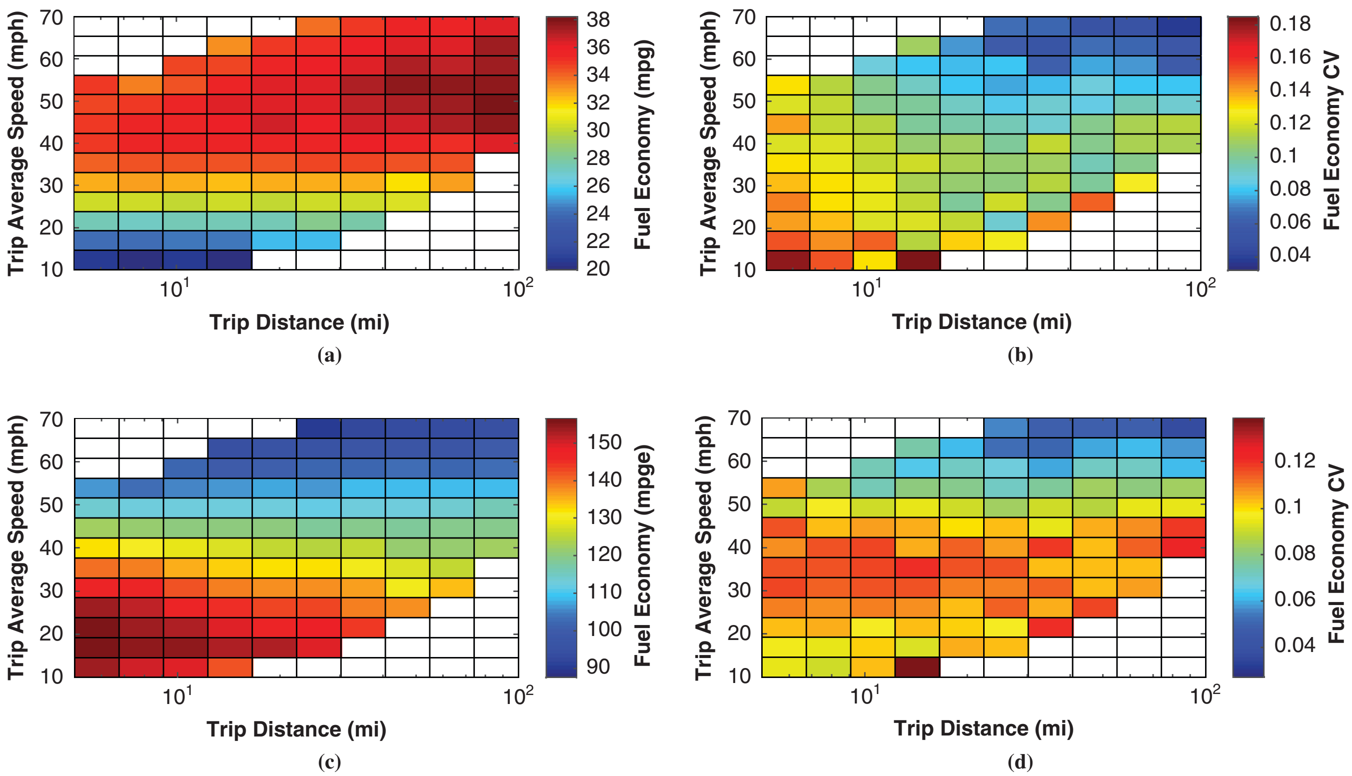

FIGURE 3 Differences in ICEV and BEV fuel economy performance by trip distance and average speed (CV = coefficient of variation).

In these tests, TripEnergy gave much better estimates of individual trip energies than either of the fixed fuel economy methods, and slightly worse estimates than the TripEnergy vehicle model does with access to the true drive cycles. For predicting individual trip energies, the TripEnergy model has a typical (root median square) percent error of 8%, substantially better than fixed fuel economy methods do with access to the same survey data, and a little worse than the 5% error for the vehicle model with access to the entire drive cycle (Figure 4*a*). Energy estimates are relatively unbiased across trips with different average speeds, unlike predictions based on a vehicle's average fuel economy, which significantly underestimate energy use at low speeds (Figure 4*b*). To measure the accuracy of the vehicle model, its estimates are compared with ADVISOR's (Figure 4*c*). TripEnergy fuel economies have a 0.97 correlation with ADVISOR values despite being significantly less computationally intensive (~700 × faster). Estimated fuel economies differ from ADVISOR's with a standard deviation of 2.2 mpg. To see how geographically representative the GPS data are, the researchers tested whether proxy drive cycles sampled from one location can be used to estimate energies for trips in another location (Figure 4, *d* and *e*). To provide a null model, the same test was performed letting proxy drive cycles come from any location. The location of origin for the proxy drive cycle makes little difference to estimation accuracy.

In Figure 4, the EPA mpg method assumes that all trips have the fuel economy estimated by EPA. The avg. mpg method assumes that all trips have the average mpg of the sample of survey trips. For reference, included are energy estimates from using the vehicle model component of TripEnergy on the true drive cycles of the survey trips, which are treated as unknown in the other three methods. Figure 4*a* shows estimation errors for the total energy of all survey trips and the energies of individual trips. Avg. mpg achieves zero total energy error because it has been optimized to reproduce the total energy of the survey sample. Figure 4*b* shows a comparison of fuel economies estimated by the vehicle model component of TripEnergy with fuel economies estimated by microsimulation. Figure 4*c* shows energy error for individual trips binned by average speed. Solid lines show the average error, while shaded regions show the range of errors corresponding to the middle 80% of trips. Figure 4, *d* and *e*, shows the accuracy of estimating trip energies in one location using drive cycles from all other locations. The top panel shows root median square error for individual trips, and the bottom panel shows error for the total energy of a set of trips. In the null model, drive cycles from all regions are used to make estimates of energies in all regions.

APPLICATIONS

The model here enables a variety of applications that are not easily done with existing methods. Several applications are outlined, as follows.

Enriched BEV Range Estimates

Official range estimates for BEVs are designed to be accurate on average, but they make little allowance for variation in driving conditions. Estimates are currently based on predictions of a vehicle's average fuel economy under city and highway-style driving. But potential customers interested in purchasing a BEV may also wish to know a worst-case range. TripEnergy could be implemented in an app or online tool, allowing users to estimate, for example, a range below which a trip or series of trips would exceed battery

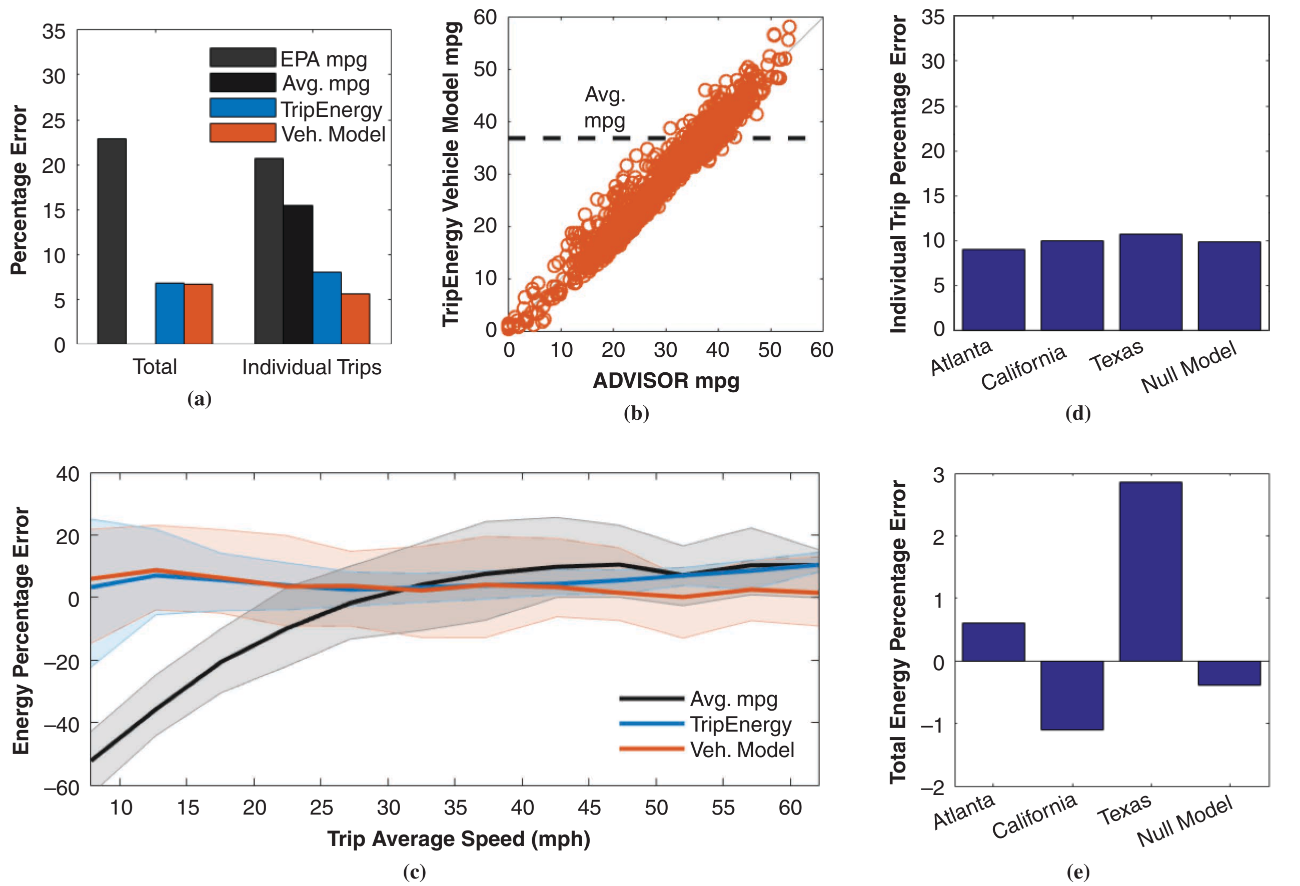

FIGURE 4 Accuracy of TripEnergy and two other methods applied to 2,000 simulated survey trips (Veh. = vehicle).

capacity with a given low probability. Since range varies with ambient temperature, range estimates could be tailored to a region's climate and disaggregated seasonally. Range estimates could also be compared with typical daily driving distances in a given city or area where the vehicle is sold.

BEV Charging Effects on the Electric Grid

TripEnergy could help electricity providers and regulators predict the impacts on the electric grid of a fleet of electric vehicles charging. Providers could run the TripEnergy model, assuming an expected electric vehicle fleet to predict the timing and intensity of grid demand based on daily driving distances, when trips start and stop, and weather. This ability would let electricity providers and regulators better understand the secondary effects of widespread BEV adoption, such as weather-related spikes in residential and transportation energy consumption.

Energy Savings from Changes to Driving Behavior

The model presented here would allow drivers and policy makers to better understand the potential for energy savings from changes in driving behavior. Studies have shown that some savings can be achieved simply by reminding travelers about the energy and emissions impacts of their travel choices (*43*). TripEnergy is computationally inexpensive and could be integrated into a smartphone application, with estimates for planned or past trips displayed to drivers in real time, with city, neighborhood, or social network–level comparisons.

Energy Savings from Changes to Vehicle Performance and Technology

TripEnergy was recently used to study how improvements to battery capacity would affect BEV range, showing that expected battery improvement will practically eliminate the difference between urban and rural areas in the portion of vehicle days that are covered on a single charge (*37*). Vehicle manufacturers and regulators could use the same approach to study how much energy savings could be realized from improvements to vehicle mass or drag, for example, with results that can be made specific to particular locations. TripEnergy draws on a richer variation in driving conditions than can be obtained from standardized drive cycles, which makes it more suitable to assessing the benefits of potential improvements under real-world usage. This ability could help manufacturers to prototype and evaluate vehicle designs efficiently.

SUMMARY

Personal vehicles contribute significantly to energy use and environmental impacts at local and national scales. Relating aggregate impacts to low-level determinants, such as vehicle technology and driver behavior, is key to informing environmental policy and technology planning. The TripEnergy model presented here accomplishes this by reconstructing second-by-second driving behavior across the United States in a way that matches nationwide travel patterns. A demand model pairs trips from a nationally representative travel survey with GPS-based drive cycles and time- and location-based temperatures. This information is fed into a vehicle model that computes energy use and covers a wide range of vehicles. A distribution of energy requirements for single trips can be generated based on known information about a trip's distance, region, and time and date of travel. The estimate is more accurate than one based on distance alone, without requiring the detailed information about its route and speed history. More accurate aggregate energy estimates can then be made using travel surveys that are representative of the traveling population.

TripEnergy contributes to multiple communities studying personal vehicle travel, including energy and environmental researchers, transportation researchers, policy makers, and vehicle manufacturers. The model is expected to be particularly useful where analyses depend on variations in vehicle performance and temporal, regional, or socioeconomic patterns of travel behavior, and where impacts are likely to change with continued evolution in vehicle technology. Aiding such analyses should help inform environmental policy and technology planning, while addressing consumers' travel needs.

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