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

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ABSTRACT

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 typically 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. Here we introduce a model for estimating privately operated vehicle energy consumption, TripEnergy, that accurately reconstructs detailed driving behavior across the U.S. and simulates vehicle performance for different driving conditions. 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, we expect it to be useful for a variety of applications, including technology assessment, cost and energy savings from eco-driving, and the integration of electric vehicle technologies into the grid.

INTRODUCTION

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

A variety of methods have been used to estimate the energy use of single trips or larger populations. Top-down methods such as energy sales accounting provide data on large-scale environmental impacts 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 specific vehicle performance and driver behavior, but rely on data that is not available at the macro scale needed to understand the societal impacts of policies.

Relating aggregated energy-related impacts, such as greenhouse emissions, to low-level factors is similarly critical. Privately operated vehicles (POVs) are one of the primary emitters of greenhouse gases in the U.S., and reductions to the energy- and carbon-intensity of transportation are 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 the plausibility of emissions targets means relating them to required levels of technology, infrastructural, or behavioral changes necessary to meet these goals.

In this paper we present a tool for estimating POV energy consumption that is designed to be applicable to this wide range of uses. The method, TripEnergy, produces accurate estimates for energy aggregates consistent with top-down inventories (e.g. total gasoline consumption), but computes them from the bottom-up based on second-by-second reconstructions of driving patterns across the U.S. 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 vehicle models, and 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. The tool produces coherent results with different levels of detail in its inputs, for a wide range of vehicle models, and in a computationally tractable way. It allows more coverage and accuracy than models based only on GPS surveys or direct vehicle modeling, but can address a wider range of questions than possible with fleetwide emissions models.

BACKGROUND

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

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 U.S., the EPA requires fuel economy labeling of all new personal vehicles. These are derived from a series of dynamometer tests (*8*) in which a vehicle is driven through several standardized drive cycles (*9*). These estimates 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 has also been used to capture variation in operating conditions. Various software packages simulate vehicle operation over an input drive cycle (*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 based on a single miles per gallon (MPG) estimate cannot directly capture variations in energy use with driving style (*18*) or climate (*19*). By using a single energy intensity value, these methods will introduce biases for congested city driving, for example, or moderate speed highway driving, conditions that are likely to have particularly high or low energy intensity (*17, 20, 21*). Dynamometer testing and onboard measurement can provide data for these more extreme conditions, but data collection is impractical for analyses of very 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 U.S. for example, the Federal Highway Administration (FHWA) (*22*) collects data on statewide and national gasoline consumption from gas tax receipts, and converting barrels of oil to energy consumption and CO_2 emissions. For well-mixed greenhouse gases this approach is often deemed accurate enough for modeling and inventory purposes. Other uses of top-down accounting include extrapolating future trends in gasoline consumption from fleet-average fuel economy and vehicle miles traveled (*23*), and constructing localized emissions inventories. For example, Gately et al. use roadway level VMT data to create a high-resolution spatial inventory of U.S. transportation-related greenhouse gas emissions (*24*).

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

Hybrid methods

Combining large and 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. These 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*). Other approaches have been to generate synthetic drive cycles from travel demand models and combine them with vehicle simulation (*21, 28*), or to directly link microscopic travel demand simulations with detailed vehicle models (*29*).

These simulations are a common way to estimate the energy impacts of changes to the transportation network or travel demand. However, they are not typically designed to address technological change or modifications to driving behavior. Energy consumption in these models is often calibrated using 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 the emissions or energy intensities of each link of the road network, rather than driver- or vehicle-based intensities. A road-based energy accounting makes it difficult to observe the energy need of individual vehicles over the course of a day.

MODEL REQUIREMENTS & APPLICATIONS

The tool that we describe in the next section 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, for national aggregates, and for various levels of aggregation in between.

Energy requirements vary greatly from trip to trip due to variations in vehicle technology, driving style (*18*), and ambient temperature (*19*). Accounting for these variations allows fuel economy to vary in a realistic way with trip characteristics, allowing a number of applications that require location-, time-, and trip-resolved energy estimates. Additionally, because trip-by-trip energy consumption is highly variable, we would like our method to be able to 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. Bridging these data types allows analyses that run across scales, i.e. 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 to those in the inner core of a city.

Our 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 is infeasible to gather at the large scales provided by nationally-representative travel surveys. Furthermore, every vehicle type has distinct performance characteristics that strongly influence energy use.

The TripEnergy model presented below was developed to meet 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 is able to 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 U.S. at high resolution.

Applications

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

Enriched BEV range estimates

Official range estimates for BEVs are designed to be accurate on average, but 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 may also wish to know a 'worst case' range. TripEnergy could calculate this, for example, as a range below which a trip or series of trips would exceed battery 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. Ranges estimates could also be compared to 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. The timing and intensity of grid demand could be predicted 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 policymakers 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 (*36*). TripEnergy is computationally inexpensive and could be run on a smartphone, 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

We recently used TripEnergy 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*). The same approach could be used 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, making it more suitable to assessing the benefits of potential improvements under real-world usage. This ability could help vehicle manufacturers evaluate vehicle designs quickly.

MODEL

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

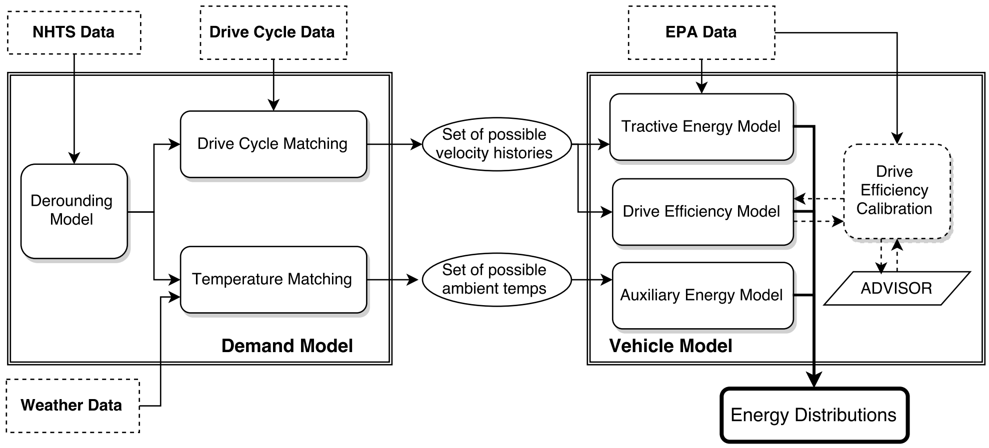

FIGURE 1 : TripEnergy model diagram, showing the demand model (left) and vehicle model (right). The demand model combines travel survey data (e.g. National Household Travel Survey) with higher resolution GPS-based drive cycles and weather data to reconstruct a second-by-second picture of vehicle operating 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*).

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 us supplement broad survey data with the detailed description of trips needed to estimate energy consumption.

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

Demand Model

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

Trip distances and times from NHTS are self-reported, and travel surveys have shown evidence of rounding and other reporting errors (*38*). 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 (*37*) this function can then be used to estimate the distribution of the original unrounded distances and times.

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 an observed trip could have had. In the

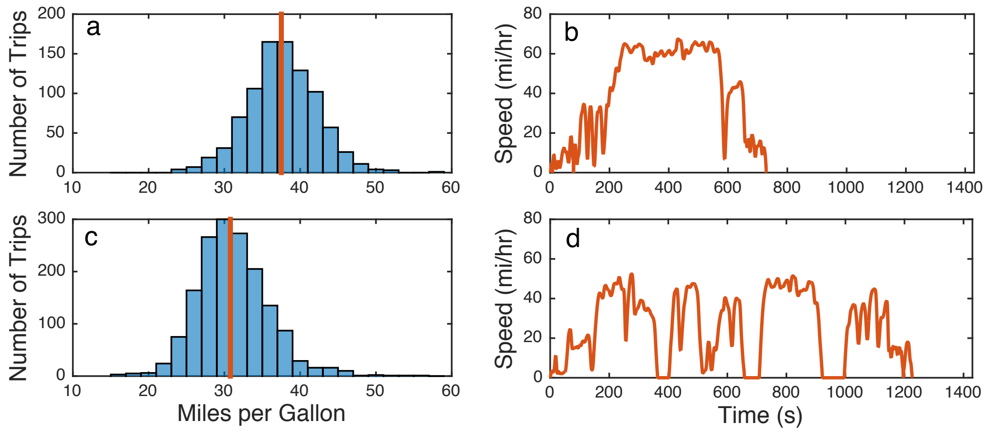

FIGURE 2 : Example of the effect of trip duration on the fuel economy of the 2014 Ford Focus. The right column shows two drive cycles corresponding to 8-mile trips, with durations of 10 minutes (b) and 22 minutes (d). The left column (a,c) shows the distribution of fuel economy values for similar trips 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.

drive cycle matching component, we link each trip with a set of similar GPS drive cycles. The drive cycle matching draws from a GPS database with 117,588 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. We found this procedure sufficiently differentiates between different types of trips with different energy requirements, as illustrated in Figure 2.

Trips are also linked with a range of external temperatures. Using an approach similar to Yuksel et al. (*14*), each NHTS trip is first paired with a weather station in the Typical Meterological Year (TMY3) 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 TMY3 database according to the reported month and time-of-day of the trip.

The set of all linked driving conditions measure a range of 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 below, leading to a probability distribution for energy requirements of each NHTS trip.

Vehicle Model

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

A trip's tractive energy can be computed from drive cycles received from the demand model using standard models of vehicle motion, with tractive power output of a vehicle given as a function 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 are dynamometer or coastdown coefficients published by the 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 $\mathscr{E}_{tr}$ for the trip.

Conversion losses are significant for all POVs. (An internal combustion engine 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 as a polynomial function (*39*). Rakha et al. (*40*) present a related method using EPA test result data to fit this function. Our approach is similar, and uses a fitting approach first proposed by Lutsey (*41*) that exploits data from EPA CAFE fuel economy tests. A trip's total energy consumption ΔE_B and tractive energy consumption E_{tr} can be calculated from reported unadjusted MPG ratings, the CAFE drive cycles, and a vehicle's dynamometer coefficients. Using the formulation for total energy described above, η_{drive} can then be calculated for a particular CAFE drive cycle as

$$\eta_{drive} = \frac{\mathscr{E}_{tr}}{\Delta E_B - \frac{\mathscr{E}_{aux}}{\eta_{aux}}}. \tag{1}$$

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

Similarly, pre-conversion auxiliary energy is factored into final auxiliary energy delivered to auxiliary systems and the auxiliary efficiency: $E_{aux} = \mathscr{E}_{aux}/\eta_{aux}$. In typical driving most auxiliary energy use comes from climate control (*42*). The external temperature received from the demand model determines how hard climate controls must work to maintain cabin temperature within a comfortable range. We model HVAC energy consumption with a steady-state heat balance model: $P_{thermal} = k|\Delta T|$, with the thermal constant k taken to be 350 W/Cdeg. 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). We add a constant power of 250 W to power other auxiliaries such as dashboard lights and power steering (*43*). The efficiency η_{aux} is taken to be a constant for each powertrain type. (Equal to 0.185 for ICEVs, 0.81 for BEVs, which take into account typical powertrain effiency and power conversion losses. See Needell et al. (*37*) Supplementary Information.)

MODEL VALIDATION

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

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*). The need for adjustment factors is thought to arise from differences between the drive cycles used in the tests and real-world drive cycles. However, the method here produces estimates close to adjusted fuel economies without the need for adjustment factors. After using the EPA test results to calibrate drive efficiency, the model can be applied to a broad set of realistic drive cycles that are representative of real-world driving to measure fleetwide performance. The model has been calibrated on two ICEVs and two BEVs and 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*).

Reproducing EV and ICEV performance behavior

BEVs and hybrid electric vehicles (HEVs) 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.) We see a strong dependence on average speed in agreement with expected performance for both vehicle types. We see a secondary dependence on trip distance where, for a given average speed, fuel economy tends to increase with trip distance for an ICEV but decrease for a BEV. This is occurs because longer distance trips tend to include more highway driving.

In addition, the method here can be used to 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 (*37*), we exploit this capability of TripEnergy to evaluate the way BEV range is different for rural and urban drivers.

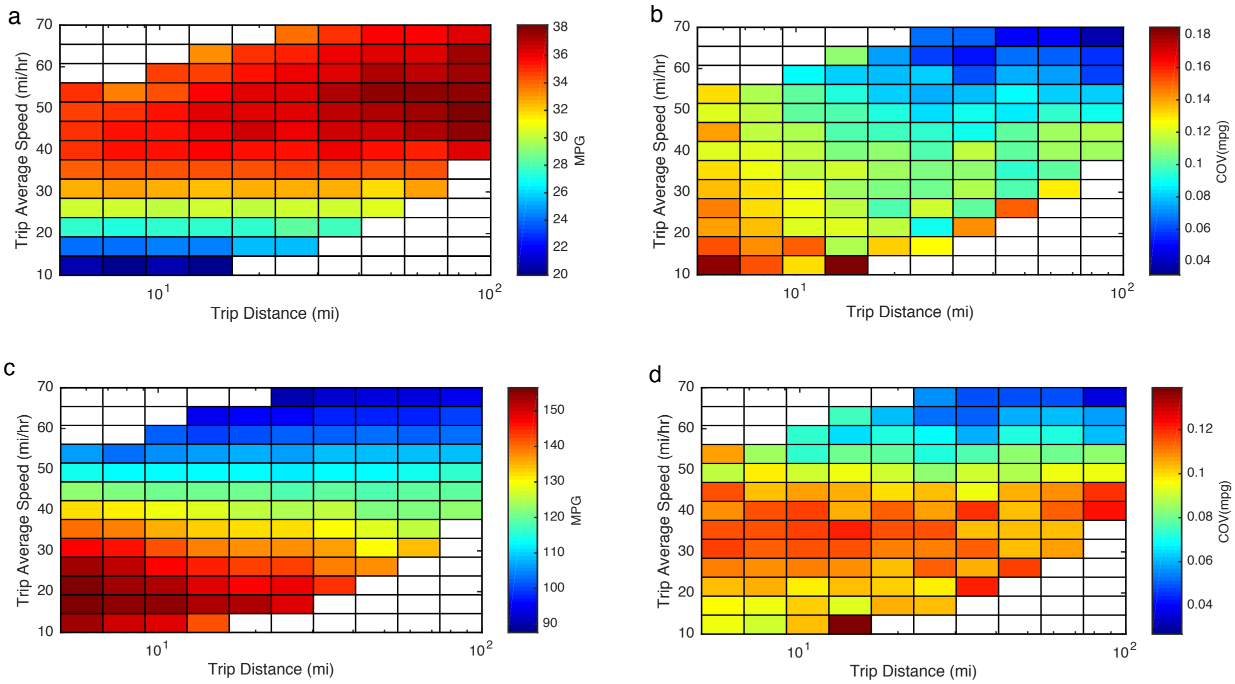

FIGURE 3 : Differences in ICEV and BEV fuel economy performance by trip distance and average speed. Top plots are for the 2014 Ford Focus (an ICEV) and bottom plots are for the 2013 Nissan Leaf (a BEV). The left column shows the average fuel economy, in units of miles per gallon (MPG) for the Focus (a), 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.

Single trip energy and aggregate energy estimation

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

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

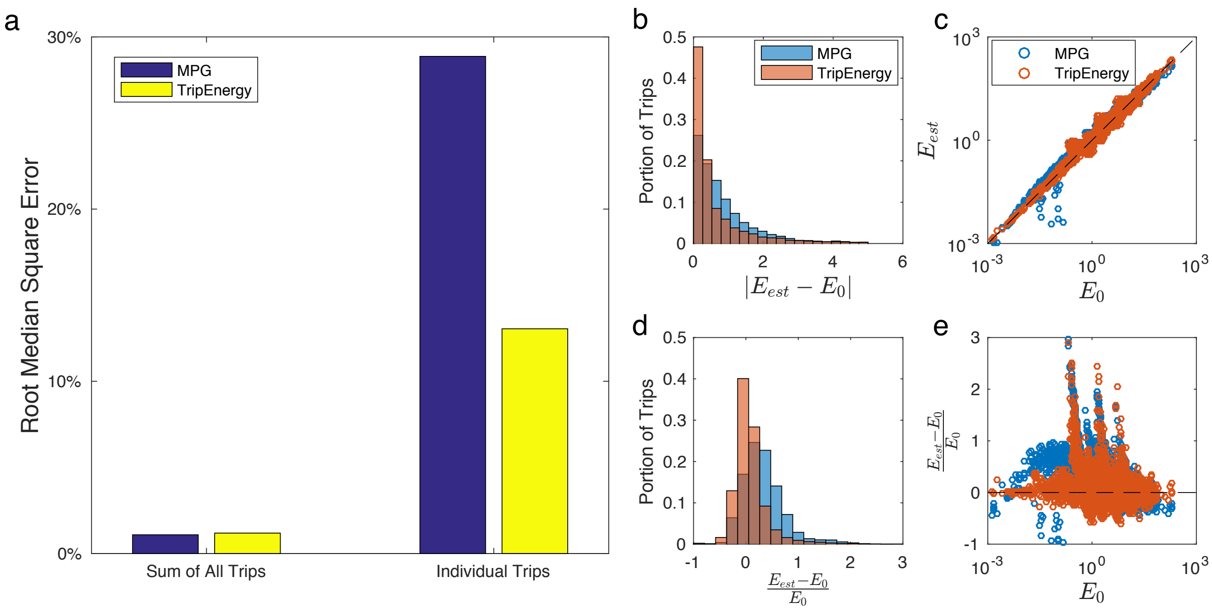

FIGURE 4 : Cross-validation of TripEnergy's accuracy and comparison with a method based on average fuel economy (the MPG method). TripEnergy was used to estimate the energy of a test set of GPS trips using only the distance and duration of the trip. Energy estimates were also made using the MPG method. 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.

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

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 accurately reconstructing second-by-second driving behavior across the U.S., giving a detailed yet expansive view of 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 realistic distribution of energy requirements for single trips can be generated based on known information about a trip's distance, region, time and date of travel. Aggregate energy estimates for large numbers of trips draw on 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. We expect the model to be particularly useful where (i) analyses depend on variations in vehicle performance and temporal, regional, or socioeconomic patterns of travel behavior, and where (ii) impacts are likely to change with continued evolution in vehicle technology. Aiding such analyses should help inform environmental policy and technology planning, while addressing consumer's travel needs.

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