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**Title:**

# Analyzing the Energy Consumption of the BMW ActiveE Field Trial Vehicles with Application to Distance to Empty Algorithms

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**Abstract**

In the development of environmentally friendly urban mobility, the shift away from non-renewable energy sources presents numerous challenges. Electric vehicles (EV) can facilitate such a transition, while also reducing local pollution and noise in dense urban environments. However, the technical constraints of energy storage and recharging create a need to better understand how consumers use their vehicles and exactly how these vehicles consume energy.

BMW has conducted two extensive field trials as part of the development of its production electric vehicle, the i3. The first trial, the MINI E, was a three-year study of approximately 600 converted MINI vehicles. The second, the ActiveE, is also an EV conversion but based on the BMW 1 Series Coupé with approximately 1000 converted vehicles. This paper first introduces the ActiveE field trial and provides an overview of the project's scope and methods for data collection. Next, it analyzes the energy consumption of each ActiveE vehicle over a period of approximately one year. In particular the data analysis is used to better understand the challenges in estimating an EV's Distance to Empty ($D_{TE}$), which is defined as the actual distance the vehicle can be driven before recharging is required. The importance of an accurate $D_{TE}$ was shown in a previous MINI E user study, which concluded that users would rather have a more accurate estimate of $D_{TE}$ than an increase in battery capacity.

This research shows that the main task of a $D_{TE}$ algorithm is to estimate the future energy consumption of the vehicle. There are many coupled factors that affect the future energy consumption, which makes it difficult to predict using physics-based models. Conventional algorithms avoid using physics-based models by measuring past energy consumption and assuming that the future energy consumption will be similar to the past. However, the ActiveE dataset shows that this is not always a valid assumption: approximately 15% of the time the energy consumption changed by 30% or more between subsequent Drive-Charge events. For conventional algorithms, the $D_{TE}$ estimation error is large when there are significant changes in energy consumption from the past to the future. Thus this research attempts to quantify the changes in energy consumption between subsequent Drive-Charge events. The ActiveE data showed that auxiliary energy consumption (e.g. heating, defrosting, etc.) was significant and changed the most between Drive-Charge events. This means that an effective way to improve $D_{TE}$ algorithms would be to incorporate estimated changes in auxiliary energy consumption.

**Keywords:** electric vehicles, fleet vehicles, field trials, energy consumption, distance to empty, range algorithms

## 1 Introduction and Overview

BMW has conducted two extensive field trials as part of the development of its production electric vehicle, the i3. The first trial, the MINI E, was a three-year study of approximately 600 converted MINI vehicles in the United States, Mexico, Brazil, Germany, the United Kingdom, France, China, Hong Kong, Japan and South Africa. The second, the ActiveE (Figure 1), is also an EV conversion but based on the BMW 1 Series Coupé. There are approximately 1000 vehicles with the majority in the United States but also in Germany, the United Kingdom, the Netherlands, France, Switzerland, Italy, China, Japan and South Korea.

Section 2 provides a review of the literature related to field trials of electric and/or hybrid vehicles and explains why research organizations are recognizing the need to better understand in-use energy consumption. Other field trials are discussed along with behavioral issues related to Distance to Empty ($D_{TE}$) estimation. Section 3 introduces the ActiveE field trial and provides an overview of the project's scope and methods for data collection. Section 4 presents a subset of the ActiveE data over a period of approximately one year. Finally, Section 5 uses this data to better understand the challenges in estimating an EV's $D_{TE}$.

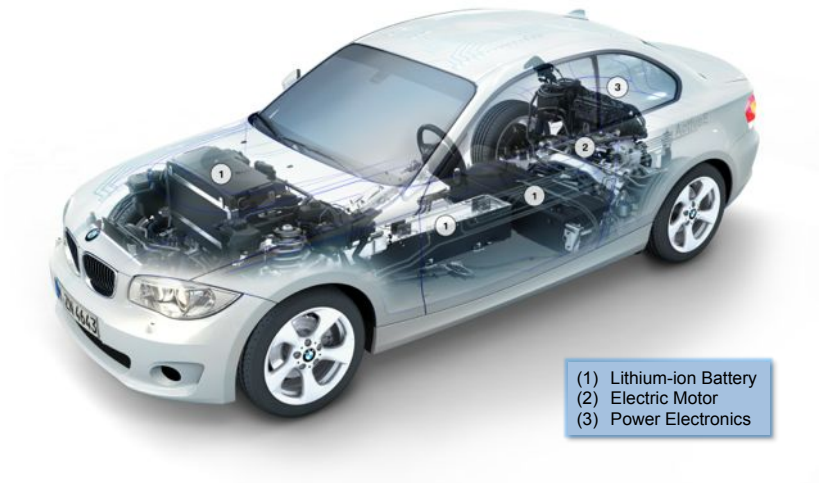



Figure 1: BMW's ActiveE is an EV conversion based on the BMW 1 Series Coupé.

## 2 Literature Review

Understanding real-world, in-use energy consumption presents challenges for vehicles powered by gasoline and/or electricity. In the United States, fuel economy (CAFE) regulations assume that gasoline vehicles will fall 20% short of their test-cycle fuel economy under real-world conditions. EVs and PHEVs are estimated to further deviate from test-cycle

energy consumption, with the on-road “gap” between real-world and test-cycle energy consumption estimated at 30% [1]. Researchers have recently observed that test-cycle energy consumption is decreasingly representative of actual energy consumption [2]. As a result, the International Council on Clean Transportation (ICCT) and other research organizations have recognized the need to better understand in-use energy consumption.

### 2.1 Studies of PHEV and EV energy consumption

While plug-in vehicles represent a small fraction of vehicles sold (less than 1% in most markets), published research that observes energy consumption and user behavior in larger fleets is starting to appear. Lippmann et al. reported energy consumption from one PHEV rotated among 12 households for one year but focused on charging behavior [3]. Several authors have noted the challenges in estimating and presenting energy consumption of Plug-In Hybrid Electric Vehicles (PHEVs) in a useful clear manner [4][5][6]. However, these studies of PHEVs generally emphasize charging behavior and driving distance as causal factors and focus less on vehicle-to-vehicle or temporal variation in electrical energy consumption.

A number of papers have specifically discussed observed variation in energy consumption from PHEV and EV fleets. Duoba et al showed results from a fleet of 155 Hymotion Prius conversions and reported high variability in energy consumption, focusing on road-loads, but the authors noted the influence of temperature on A/C usage and the resultant energy consumption [7]. Previous work by the author analyzed the performance of 125 plug-in hybrid vehicles and noted large variation in energy consumption from vehicle to vehicle [8]. One of the largest repositories of data on EV operation is the EV Project, which tabulates energy consumption and charging information for approximately 13,000 chargers and 21,000 vehicles nationwide in the U.S. [9].

### 2.2 Other studies of the BMW MINI E and ActiveE fleet

BMW has conducted two extensive field trials as part of the development of its production electric vehicle, the i3 [10]. The first trial with approximately 600 MINI E vehicles has been conducted over a period of 3 years [11]. In 2012 BMW introduced the ActiveE test-fleet consisting of approximately 1000 vehicles based on the 1 series coupé E82 equipped with a first series version of the components of the BMW i3. The data of the MINI E and ActiveE vehicles has been analyzed for BMW´s internal use with a focus on customer behavior and adaption with electric mobility and also various quality aspects [12][13]. A dedicated web site informs the drivers about their individual driving behavior (driving

distances, energy consumption, charging power and duration, etc.), with comparisons to the average data seen over the entire ActiveE fleet [14]

### 2.3 The importance of battery SOC in charging behavior

Several existing studies attempt to understand the relationship between battery status, energy consumption and user behavior when driving and charging EVs. Pichelman et al indicate that users have a better understanding of the energy consumption of their vehicles with increased use and are progressively comfortable using more available range [15]. However, the way that drivers use information about remaining battery energy is less understood. Several studies have attempted to describe charging behavior [16][17][18][19] and have discovered that battery State of Charge (SOC) plays a role in charging decisions, while previous work by the author models this formally and discovers a significant relationship [8]. However, it is unknown whether drivers actually use SOC or $D_{TE}$ in their decision to charge or not charge a vehicle—the two measures are correlated and both are reported in most EVs.

## 3 Data Collection and Analysis Methods

This study is based on the energy consumption of a fleet of 600 BMW ActiveE electric vehicles operated in private and commercial service for approximately one calendar year during 2012-13. In contrast to the MINI E, the ActiveE´s data collection functionality is based on the standard BMW Connected Drive Technologies. This enables a telematics-based data transfer of aggregated vehicle data including vehicle use, charging behavior, energy consumption figures, distance traveled, etc. The data is aggregated on-board by the electronic control units (e.g. the electric motor control unit, the high voltage battery management unit, etc.) before being transmitted via a built-in GSM card. This restricts the possibility to transmit momentary values. But it also removes the need for an uninterrupted GSM reception during driving or charging. However, due to limited onboard storage and incomplete GSM reception (especially in rural areas, or in parking garages) it may happen that certain details cannot be transmitted before they are overwritten with updated values. In general, an average data quality and completeness of 80-95% can be assumed.

There are many factors that affect the energy consumption of an electric vehicle; Figure 2 attempts to capture all of the factors by showing how driver decisions and options (purple) lead to energy losses (red) and storage (green). It would be ideal to measure each of the individual factors to quantitatively understand which factors cause significant variation in energy consumption. Since this level of detail was not recorded for the ActiveE due to data

storage and transmission limitations, aggregates of the vehicle's energy consumption were measured and divided into three categories:

- **Drive:** The energy consumed by the motor to propel the vehicle.
- **Regenerative:** The energy from the motor during regenerative braking. Note that these values do not include the regenerative braking efficiency (e.g. losses in the motor controller and battery), thus the actual energy stored back into the battery would be lower than these values. This is discussed below in more detail.
- **Auxiliary:** The energy consumed for climate control, power steering, lighting, entertainment, etc.
- **Total:** The sum of drive, regenerative and auxiliary energies with regenerative considered negative.

The precise meaning of the *Drive, Regenerative* and *Auxiliary* energy measurements depends on the exact location of the sensors. For example, if the energy is measured at the input to the motor, then the losses from the motor controller and battery (among others) are not included. To explain this further, Figure 3 shows the flow of energy through a generic electric vehicle and attempts to show all of the energy losses. Then Figure 4 shows a simplified version of the same diagram but with circled numbers (in red) representing the locations where energy measurements could be made. Location 1 is inside the battery and would be a measurement of the chemical energy available (similar to State of Charge). Location 2 is at the output of the battery. Locations 3 and 5 are at the input and output to the motor controller, respectively. Finally, Location 4 is at the input to the DC/DC 12V system that powers all of the auxiliary energy loads (e.g. cabin heating).

In the case of the ActiveE data, the *Drive* energy is measured at Location 5. This means that the actual battery energy used to propel (drive) the vehicle is higher than the values measured since Location 5 is downstream of the motor controller and battery losses. *Regenerative* energy is also measured at Location 5 and thus does not represent the actual increase in battery energy but rather the energy coming from the motor during braking. A "regenerative efficiency" must be used to estimate how much of the measured motor energy is converted to an actual increase in battery energy (State of Charge) during braking. For example, if 1 kWh of regenerative energy came back from the motor then 0.6 kWh would be stored in the battery when the regeneration efficiency is 0.6. The *Auxiliary* energy is determined by subtracting a measurement at Location 5 from one taken at Location 2. Thus the auxiliary energy values include the losses in the motor controller.

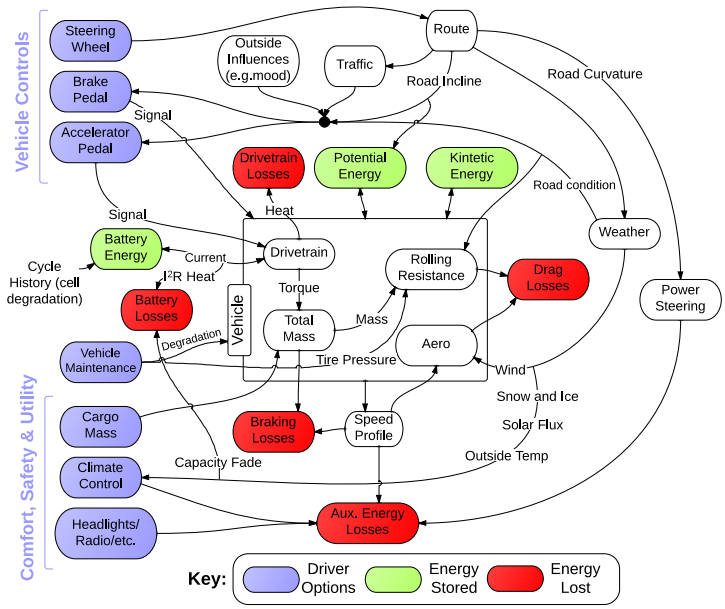



Figure 2: The above diagram shows the factors that influence a vehicle's energy consumption and specifically how various driver decisions and options (purple) lead to energy losses (red) and storage (green).

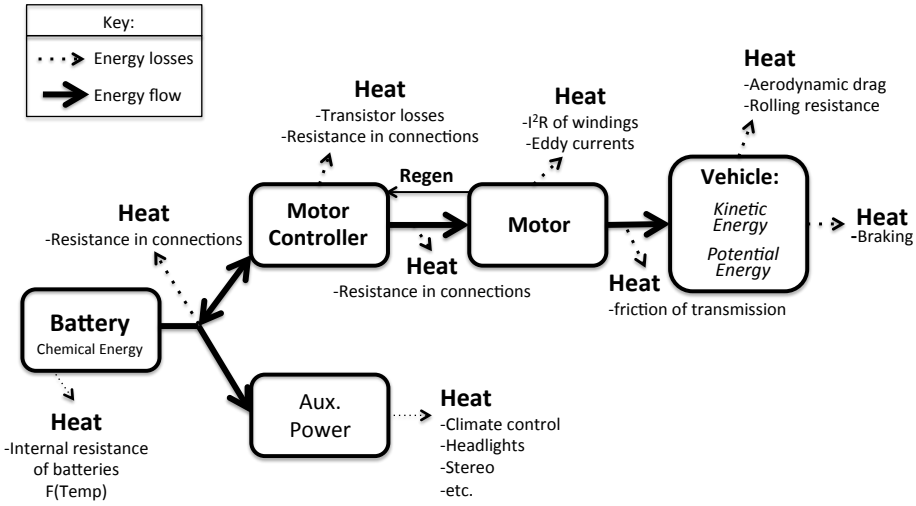



Figure 3: The energy flow through the vehicle is complex and there are a number of losses that may or may not be included in the measured value.

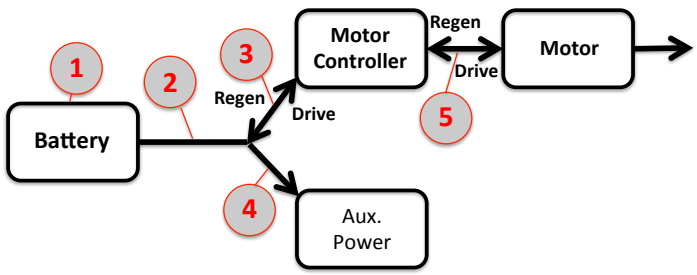



Figure 4: When discussing measured values of energy, it is important to consider the exact location of the measurement and understand which losses are included. Location 1 is inside the battery and would be a measurement of the chemical energy available (similar to State of Charge). Location 2 is at the output of the battery. Locations 3 and 5 are at the input and output to the motor controller, respectively. Finally, Location 4 is at the input to the DC/DC 12V system that powers all of the auxiliary energy loads (e.g. cabin heating).

The energy consumption was summed while the vehicle was driven between subsequent vehicle charges, which will be referred to as a *Drive-Charge* event. In other words, if the vehicle was charged, driven multiple times and then charged again, the energy values collected during the driving part of this sequence is called the Drive-Charge event. Only Drive-Charge events with a distance of 50 km or more were included in the analysis. Figure 5 shows that most of the Drive-Charge events had distances below 150 km.

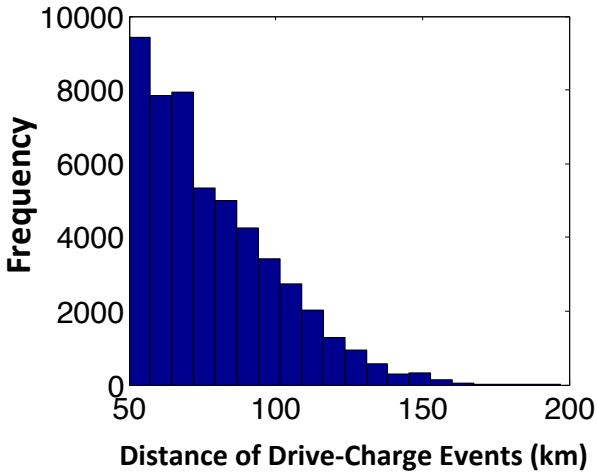



Figure 5: The energy was summed between subsequent vehicle charges, which is called a Drive-Charge event. Only Drive-Charge events with a distance of 50 km or more were included in the analysis.

## 4 Analyzing Energy Data

The objective of this section is to better understand the energy flow within the vehicle by analyzing the collected Drive-Charge data. For example, it is of interest to measure the fraction of energy that went to auxiliary loads and the variation with average vehicle speed. It is important to read Section 3 to understand the exact meaning of drive, regenerative, auxiliary and total energy.

### 4.1 Auxiliary energy

The auxiliary energy was divided by the total energy consumed for each Drive-Charge event. The results plotted in Figure 6 show it was most likely to have approximately 25% of the total energy consumed by auxiliary loads, with a probability of ~0.5 that it was greater. Also, the distribution shows that 10 to 50% of the total energy will go to auxiliary loads.

To understand the speed dependency of the auxiliary energy use, Figure 7 plots the fraction of auxiliary energy versus speed for each of the Drive-Charge events. All data within an increment of 5 km/hr were binned and averaged, which is shown as the black curve. The error bars on the curve correspond to the standard deviation calculated for the corresponding bin. The color map on the same plot represents the density of data points, which varies from

high (red) to low (blue). The color map shows that most of the data has speeds between 35 and 70 km/h. The data has an $x^{-1}$ shape with a horizontal asymptote at ~20%. This means that the auxiliary energy use increases dramatically at slow speeds because the auxiliary loads are constant even while the drive (motor) loads may be decreasing with speed.

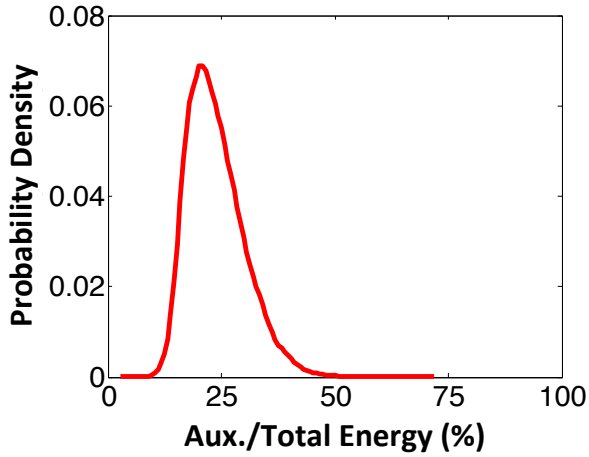
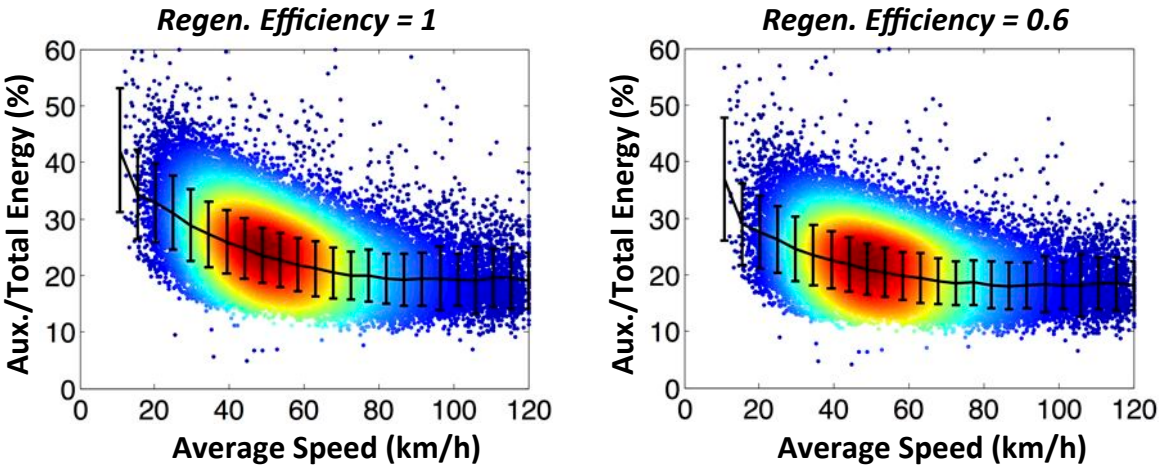



Figure 6: Driving data shows that it was most likely to have ~25% of the total energy consumed by auxiliary loads.




(a) (b)

Figure 7: The fraction of the total energy going to auxiliary loads versus speed for each of the Drive-Charge events. All data points within an increment of 5 km/hr were binned and averaged, which is shown as the black curve. The error bars on the curve correspond to the standard deviation calculated for the corresponding bin. The color map on the same plot represents the density of the data points, which varies from high (red) to low (blue). The data has an $x^{-1}$ shape with a horizontal asymptote around 20%. This means the auxiliary energy use increases dramatically at slow speeds because the auxiliary loads are constant even while the drive (motor) loads may be decreasing with speed. Plots (a) and (b) are identical except the value assumed for Regeneration Efficiency, which is explained in Section 3.

To investigate the speed dependency of auxiliary consumption further, a simple constant speed simulation was performed for a sedan-sized vehicle with a constant auxiliary load of 3kW (Figure 8). Like the experimental results shown in Figure 7, the plot has a $1/x$ shape. However, a difference is that the horizontal asymptote is at zero instead of ~20%. This dissimilarity is likely caused by the difference between the average speeds used in the

experimental data versus the constant speed used for the simulation. Even for high average speeds, the experimental data had periods of slower instantaneous speeds and possibly zero (idle) speeds where the vehicle was consuming auxiliary energy while not moving at all. All of these factors will shift the horizontal asymptote vertically.

The conclusion from this analysis is that auxiliary loads consume ~20% or more of the total energy and depend on the vehicle speed.

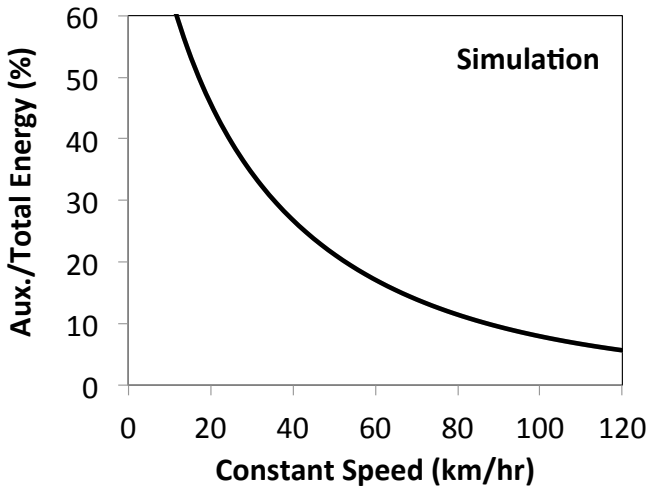
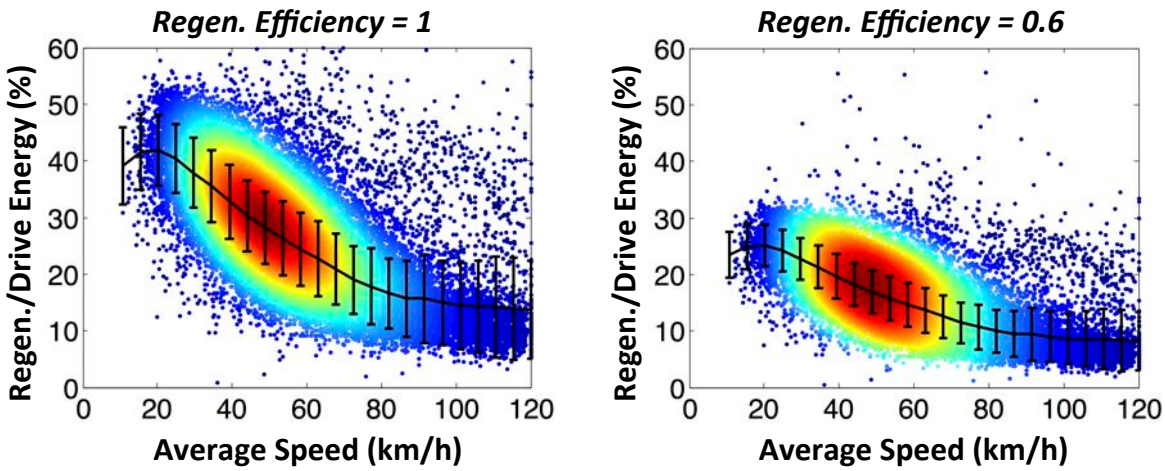



Figure 8: A simulation showing the fraction of energy consumed while a sedan-sized vehicle is driven at a constant speed with a constant 3 kW auxiliary load. Like the experimental results shown in Figure 7, the plot has a $1/x$ shape.

### 4.2 Regenerative braking

Figure 9 shows the fraction of regeneration energy versus speed for each of the Drive-Charge events. All data points within an increment of 5 km/hr were binned and averaged, which is shown as the black curve. The error bars on the curve correspond to the standard deviation calculated for the corresponding bin. The color map on the same plot represents the density of the data points, which varies from low (blue) to high (red). The data has an $x^{-1}$ shape with a horizontal asymptote around 15%. This means the regeneration energy use increases dramatically at slow speeds because there is likely an increase in braking. The slow average speeds most likely occurred in traffic and/or city conditions where more braking was required. The concave curve at slow speeds is likely an artifact from too few data points at slow speeds.




(a) (b)

Figure 9: The fraction of the total energy going to regeneration versus speed for each of the Drive-Charge events. All data points within an increment of 5 km/hr were binned and averaged, which is shown as the black curve. The error bars on the curve correspond to the standard deviation calculated for the corresponding bin. The color map on the same plot represents the density of the data points, which varies from low (blue) to high (red). The data has an $x^{-1}$ shape with a horizontal asymptote around 15%. This means that the regeneration energy use increases dramatically at slow speeds because there is likely an increase in braking. The slow average speeds most likely occurred in traffic and/or city conditions where more braking was required. The concave curve at slow speeds is likely an artifact from too few data points at slow speeds. Plots (a) and (b) are identical except the value assumed for Regeneration Efficiency, which is explained in Section 3.

## 5 Application: Distance to Empty Algorithms

An electric vehicle's Distance to Empty ($D_{TE}$) is defined as the actual distance the vehicle can be driven before recharging is required. It will be shown that $D_{TE}$ estimation error is caused by *changes* in energy consumption between the past and future. Thus this section will use the ActiveE data to explore *changes* in energy consumption between subsequent Drive-Charge events.

### 5.1 Introduction to Distance to Empty

An estimate for $D_{TE}$ is obtained using an algorithm and is displayed in real-time on the vehicle's dashboard. The maximum $D_{TE}$ for an EV is typically ~100 to 400 km less than gasoline vehicles and a full recharge usually takes hours instead of minutes [20]. Also, the energy consumption of EVs is more influenced by auxiliary loads (e.g. heating). For these reasons it is important to provide an accurate $D_{TE}$ estimate. Recent studies have shown that current $D_{TE}$ algorithms are insufficient and often cause "range anxiety" among drivers [12][21]. Predicting $D_{TE}$ is difficult because of the stochastic nature of driver behavior and the environment, the lack of a quantitative understanding for how these factors affect the vehicle's energy consumption, and the fairly basic algorithms currently being used.

Distance to Empty can be determined using [22]:

$$D_{TE}(t) = \frac{E_b(t)}{\bar{p}_f(t)} \quad 1$$

Where $E_b(t)$ is the battery energy remaining at time *t* and $\bar{p}_f(t)$ is the future average energy consumption, which has units of Wh/km or %SOC/km (SOC is the battery's State of Charge). Equation 1 shows that $D_{TE}$ can be determined if the current *and* future battery energy consumption are known. An on-board Battery Management System (BMS) measures energy consumption and thus it will be assumed that $E_b(t)$ is known perfectly. Thus the task of a $D_{TE}$ algorithm is to estimate the *future* energy consumption, $\bar{p}_f$.

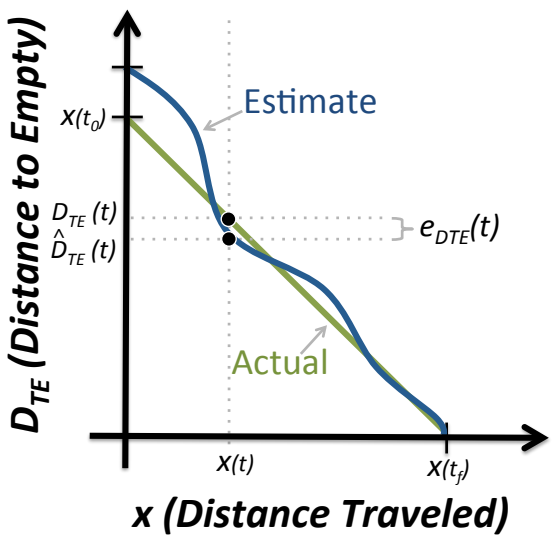



Figure 10: A schematic of the vehicle's corresponding $D_{TE}$ versus distance travelled.

A perfect $D_{TE}$ algorithm would predict a linear relationship for the actual $D_{TE}$ (Figure 10). An algorithms inability to perfectly predict $\bar{p}_f$ causes deviations from this straight line and thus $D_{TE}$ error, which is defined as (Figure 10):

$$e_{DTE}(t) \equiv \hat{D}_{TE}(t) - D_{TE}(t) \quad 2$$

Where ^ designates an estimate of the actual value.

Conventional $D_{TE}$ algorithms often assume that the future energy consumption will be similar to the past. In other words:

$$\bar{p}_f \approx \bar{p}_p \quad 3$$

Where $\bar{p}_p$ is the average energy consumption of *past* driving (e.g. 1km, running, or blended averages as described in [22]). This is considered a conventional approach since it is likely very similar to the methods being used in EVs today based on the limited amount of related

details in patents and literature [23][24][25]. The $D_{TE}$ can then be estimated by combining Equations 1 and 3:

$$\widehat{D}_{TE}(t) = \frac{E_b(t)}{\bar{p}_p(t)} \qquad 4$$

### 5.2 Changes in energy consumption

The conclusion from Equations 3 and 4 is that $D_{TE}$ estimation is more concerned with estimating *changes* in energy consumption between the past and future [22]. When the assumption shown as Equation 3 is used, the $D_{TE}$ estimation error could be large when there are significant changes in energy consumption from the past to the future. Thus this section will analyze the ActiveE data to quantify how much the energy consumption is changing between subsequent Drive-Charge events.

Using past values of energy consumption to estimate $D_{TE}$ (Equation 4) will only work if the future is similar to the past, which the ActiveE data reveals is not always the case. Figure 11 shows the probability distribution for the change in total energy between subsequent Drive-Charge events. The area shaded in green shows that there was a 15% chance that the energy consumption changed by 30% or more between subsequent Drive-Charge events. The conventional algorithms assume there is no change in energy consumption, which is shown as a Dirac Delta function in the plot.

An idealized driving cycle was used to estimate how a 30% change in energy consumption would impact $D_{TE}$ error. This driving cycle assumes that the energy consumption is constant until it increases by 30% midway through the discharge (Figure 12a). For example, assume that the vehicle is ~50 km into a full discharge when a heater load is turned on, which causes a 30% increase in energy consumption. The corresponding $D_{TE}$ error is shown in Figure 12b for the case when a running average is used to estimate $\bar{p}_f$ (Equation 4). The result is a $D_{TE}$ error of approximately 20 km at the beginning and then attenuates to zero at the end of discharge.

The *total* energy consumption shown in Figure 11a was divided into drive and auxiliary energy consumption to better understand the source of energy variation between subsequent Drive-Charge events. The results shown in Figure 11b reveal that the auxiliary energy had a broader distribution and thus experienced a larger change between Drive-Charge events. Also, a separate statistical analysis found that changes in total energy had a stronger correlation to changes in auxiliary energy. The conclusion is that auxiliary energy consumption was the most dominant source of variation between Drive-Charge events.

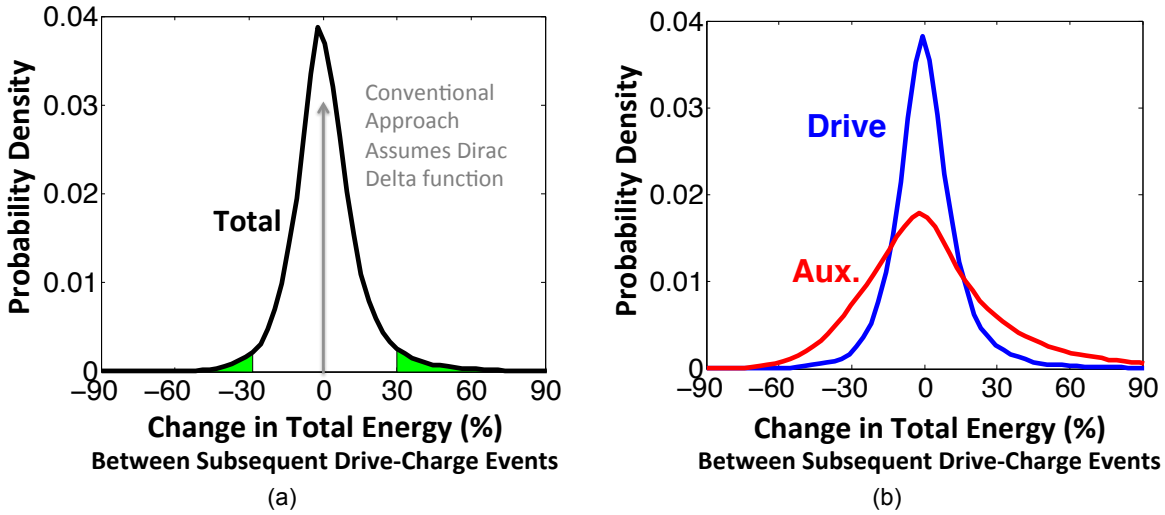



Figure 11: (a) Data showing the total energy consumption between subsequent Drive-Charge events. The area shaded in green shows that there was a 15% chance that the energy consumption changed by 30% or more between Drive-Charge events. (b) The *total* energy consumption shown in (a) was divided into Drive and Auxiliary energy consumption to better understand the source of the energy variation. The broader distribution in red shows that auxiliary energy had more variation between subsequent Drive-Charge events.

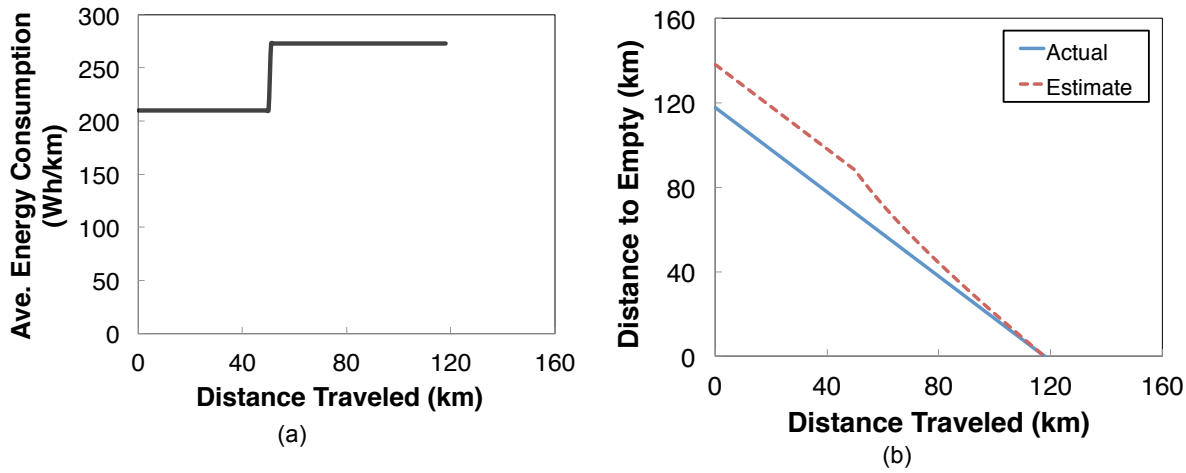



Figure 12: (a) An idealized driving cycle where the energy consumption is constant until it increases by 30% midway through the discharge. (b) The corresponding $D_{TE}$ from the idealized driving cycle. The $D_{TE}$ estimate is calculated using Equation 4 with $\bar{p}_p$ determined using the running average of energy consumption.

## Conclusions

The analysis of the ActiveE data showed that it was most likely to have ~25% of the total energy consumed by auxiliary loads (e.g. heating, defrosting, etc.). The fraction of auxiliary energy consumed versus speed has an $x^{-1}$ shape with a horizontal asymptote around 20%. This means that the auxiliary energy use increases dramatically at slow speeds because the auxiliary loads are constant while the drive (motor) loads may be decreasing with speed. The regeneration energy was found to have a similar $x^{-1}$ shape with a horizontal asymptote around 15%. This means that the regeneration energy use increases at slow

speeds because the increase in braking. The slower average speeds most likely occurred in traffic and/or city conditions where more braking was required.

An electric vehicle's $D_{TE}$ was defined as the actual distance the vehicle can be driven before recharging is required. Conventional $D_{TE}$ algorithms only use past values of energy consumption, which will only provide accurate results if the future is similar to the past. The ActiveE data revealed that there was a 15% chance that the energy consumption changed by 30% or more between subsequent Drive-Charge events. An idealized example showed that a 30% change in energy consumption could correspond to ~20 km of $D_{TE}$ error.

Auxiliary energy consumption was found to be a significant fraction of the overall energy use and had the largest variation between Drive-Charge events. This means that an effective way to improve $D_{TE}$ algorithms would be to incorporate estimated changes in auxiliary energy consumption. For example, the changes in auxiliary energy could be estimated using the outside air temperature and historical data and included in the future energy consumption estimate. This approach has been described in detail by the author in a separate publication [22].

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