NHTS Survey Day Driving Distance and Estimated Variability to Inform Electric Vehicle Range Design

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Definition and Motivation

- Plug-in electric vehicles include
  - Plug-In Hybrid Electric Vehicles (PHEVs)
  - Battery Electric Vehicles (BEVs)

- We would like to forecast and quantify impacts including
  - Gasoline consumption
  - Electricity consumption
  - GHG emissions
  - Cost
- Variability in driving distance from day to day is important
  - Without it, PHEV fuel use is underestimated, PHEV electricity use is overestimated, and BEV benefits are overestimated due to lack of “range anxiety” consideration

Image: Plug-In Toyota Prius

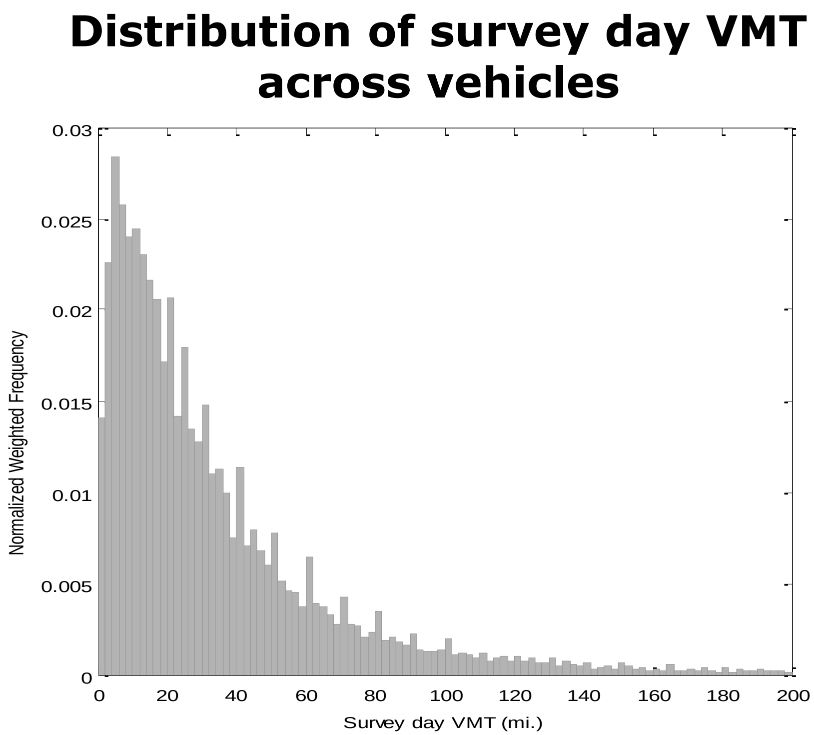
Reliance on Driving Pattern Data

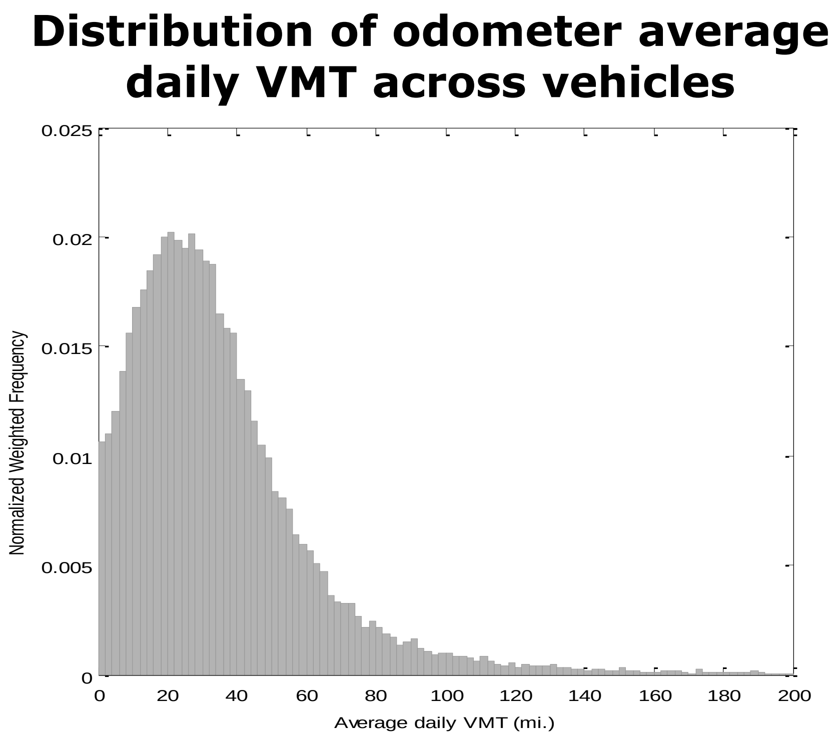
- Detailed trip data over time allows us to
  - Calculate gasoline vs. electricity consumption for PHEVs
  - Determine charging opportunities
    - And plan infrastructure deployment
  - Design vehicles, especially BEVs, with appropriate electric ranges
  - Estimate fleet penetration of PHEVs and BEVs

- This presentation focuses mainly on BEV electric range requirements
  - We assume that BEVs should meet consumer range requirements on 1 full charge per day with minimal changes to driving behavior

NHTS 2001 Data on VMT Variability

- One day of trip data per vehicle
- Two odometer readings per vehicle
- This data gives us variability in VMT **across vehicles:**

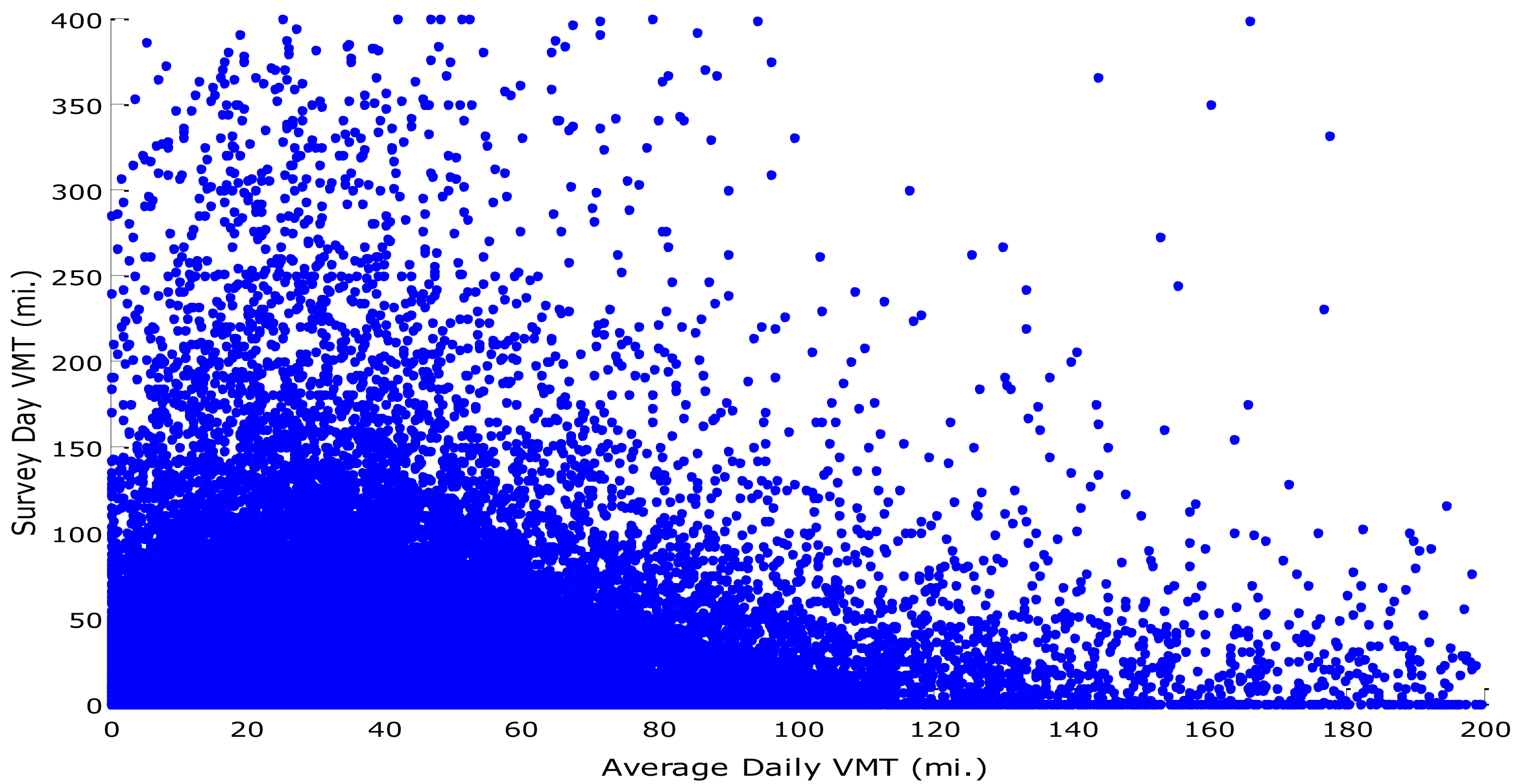




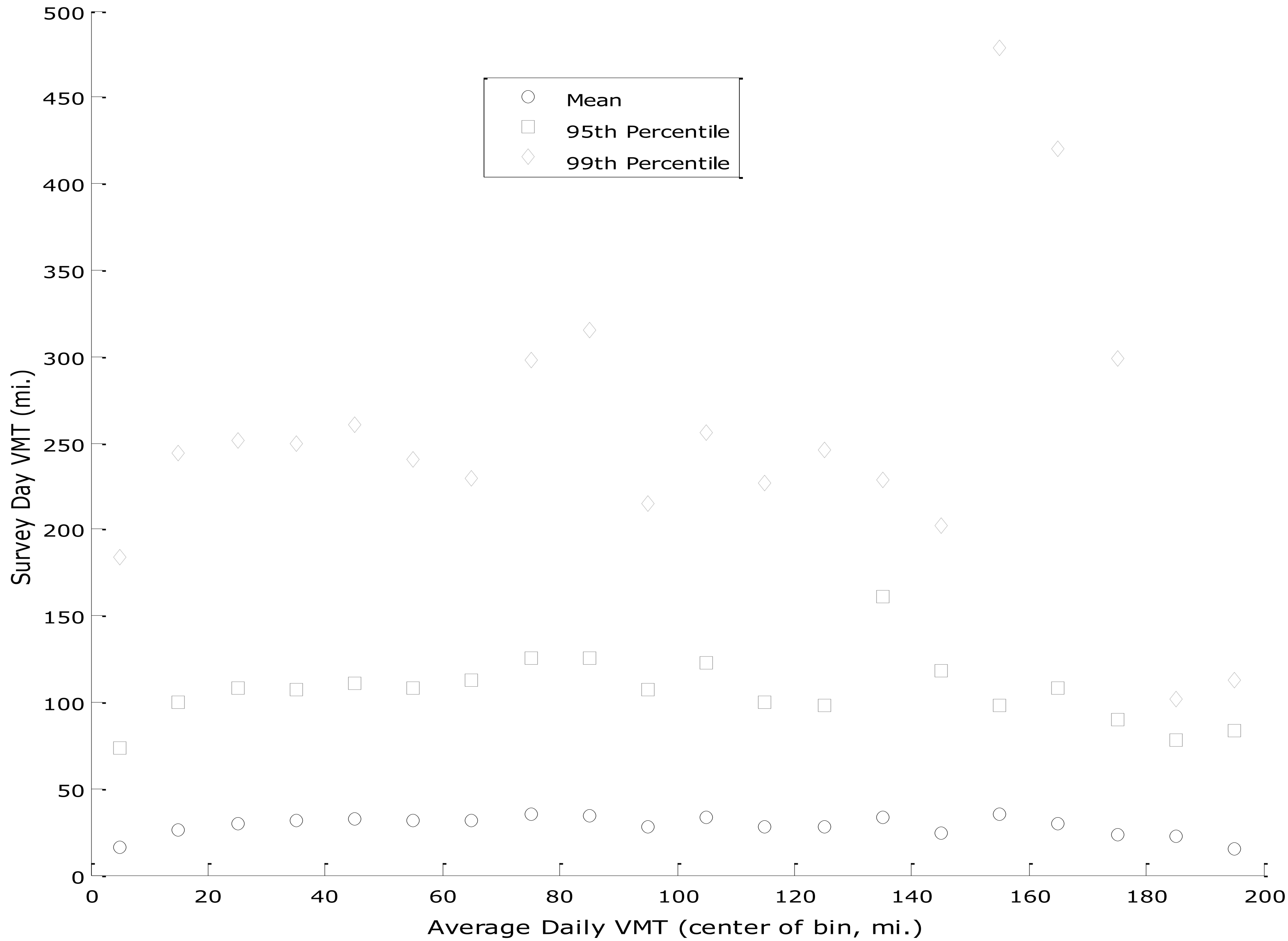
- We would like to know variability in VMT **across days**
  - As a distribution of daily VMT **for each vehicle**
  - Then as a family of these distributions, representing the fleet

Estimating VMT Variability Across Days from NHTS

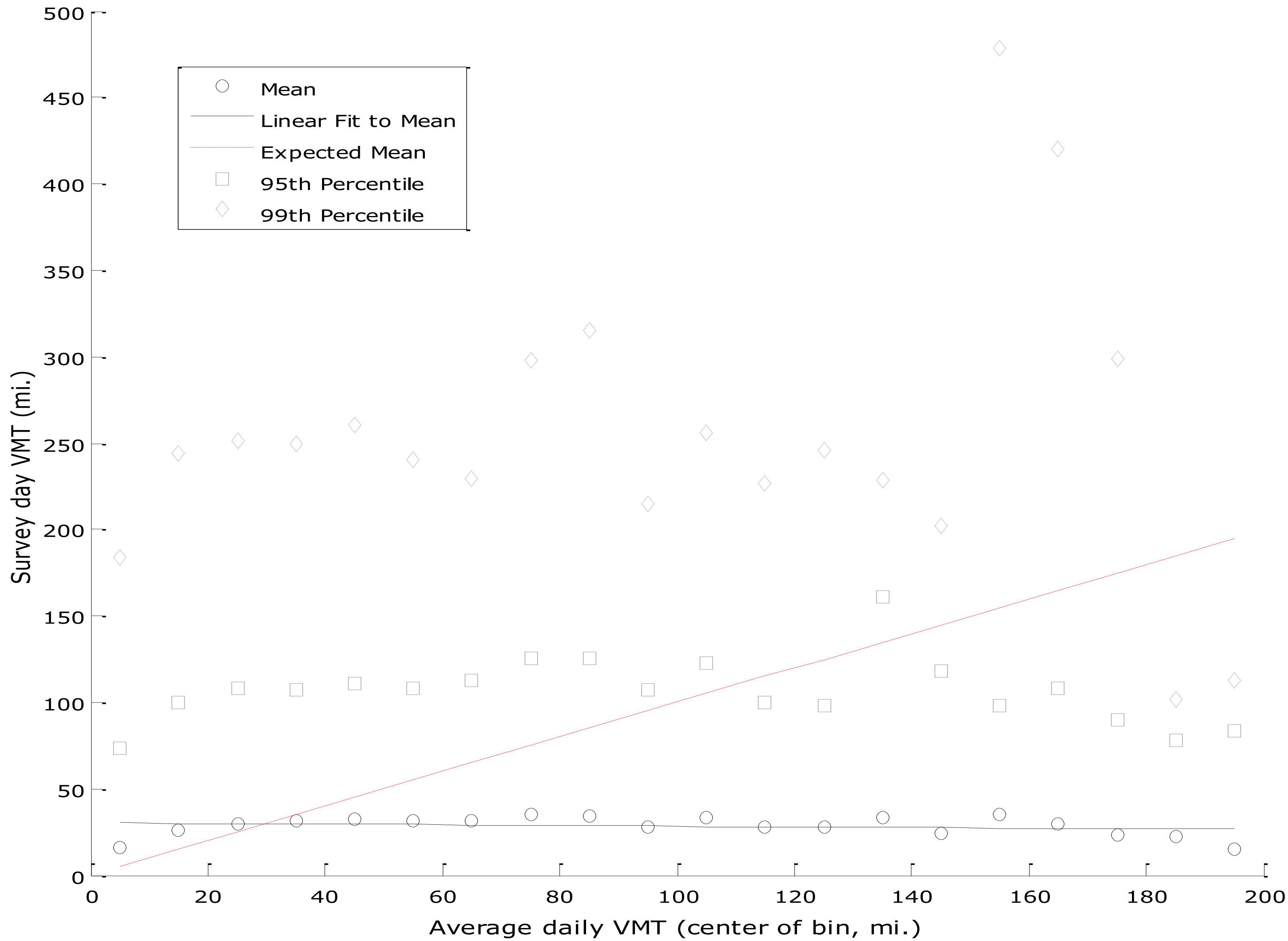
- To estimate variability in VMT across days from NHTS 2001, we
  - characterize vehicles by odometer average daily VMT
  - assume that all vehicles with the same odometer average daily VMT represent the same vehicle, on different days



Estimating VMT Variability Across Days from NHTS



Problem: Why do means not match expected trend?



Problem: Why do means not match expected trend?

- Some basic statistics confirm that the mean of the survey day VMTs is not what we expect given the odometer readings

Data Type	% Zeros	Mean (excl. zeros)	Median (excl. zeros)	Std. Dev. (excl. zeros)	Calculated Annual VMT (incl. zeros)
Survey day VMT	31.8%	33.0	22.0	33.4	**8,200**
Odometer average daily VMT	3.0%	33.3	27.8	27.1	**11,800**

- What could explain this issue?
  - Decreasing amount of data as odometer average VMT increases?
  - Selection or response rate bias towards shorter survey day VMT?
    - Do people with both high average VMT and high survey day VMT systematically refuse to answer the survey, or underreport trips?
  - Are some odometer readings incorrect, resulting in inflated odometer annual VMT estimates?
  - Lack of control for temporal issues such as 9/11, fuel prices, etc.?
  - Is there some other explanation?
- Since we don't know, we would rather not rely on this model.

Comparing NHTS Variability Estimate to MN Detailed Data

- Through our coauthors at Ford, we also had access to a set of detailed trip data for 133 vehicles from Minnesota, with hundreds of days of data for each vehicle
  - Thanks also to Mike Tamor at Ford for access to the data
- MN data was not guaranteed to be representative, but the statistics match well with NHTS odometer average VMT data and U.S. EPA estimates of average annual VMT:

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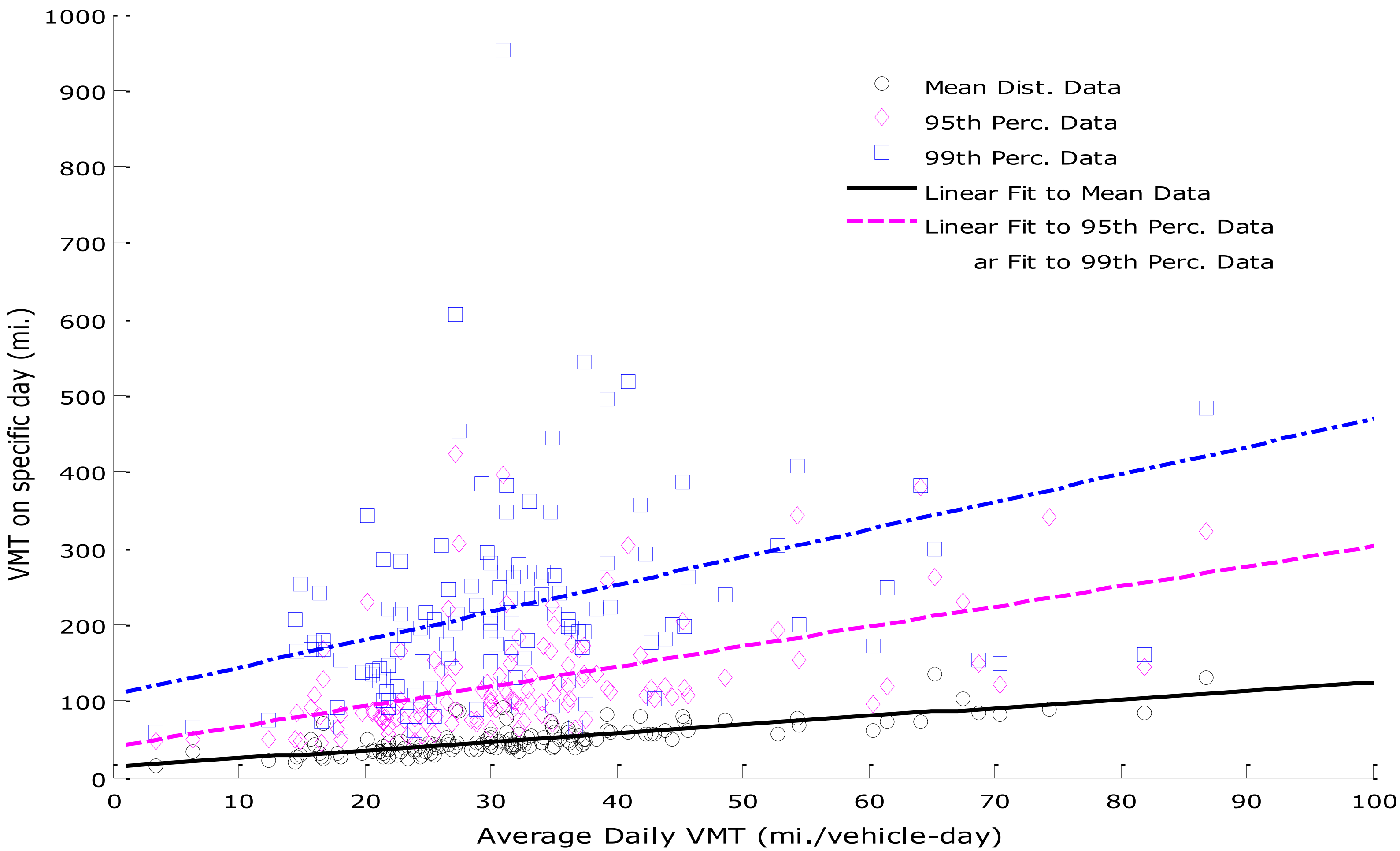
MN Average Vehicle-Day VMT	34.5%	47.0	35.8	49.3	**11,300**
MN “Odometer” Average Daily VMT	0%	32.5	30.5	14.2	**11,900**

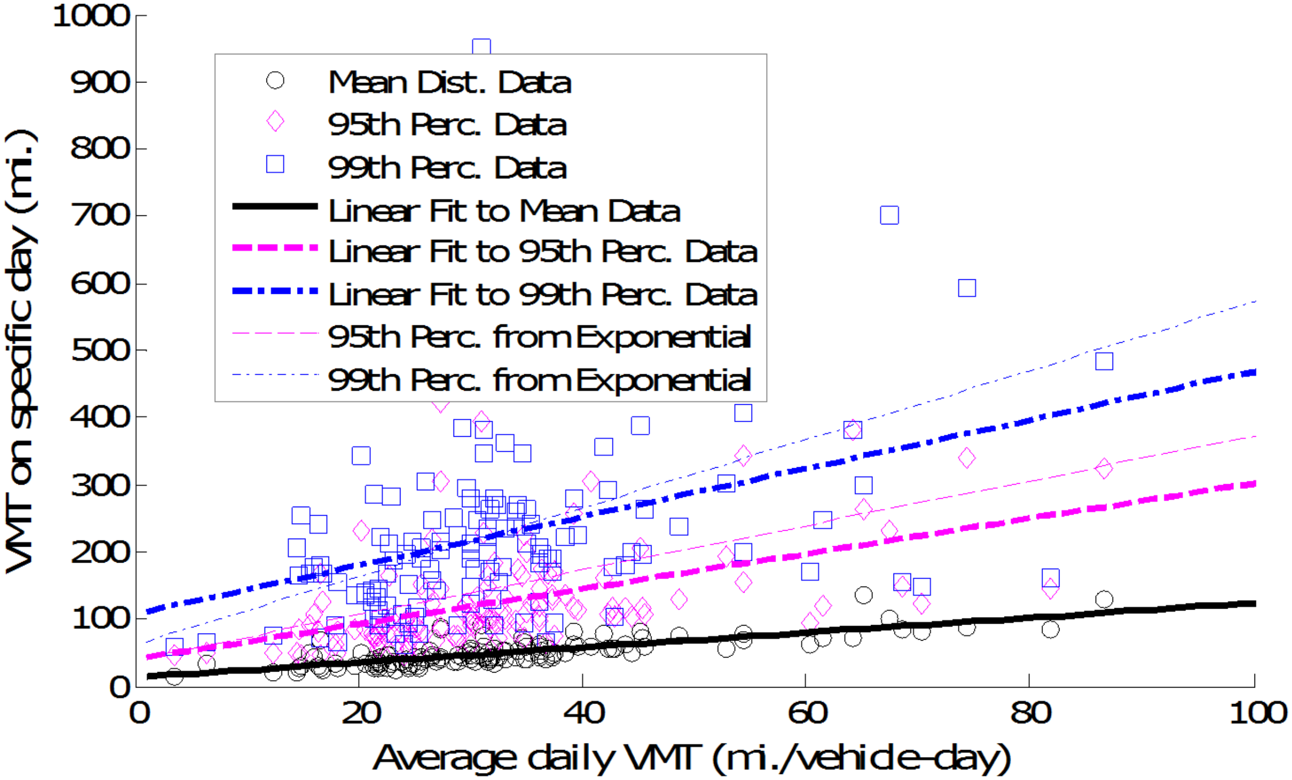
Comparing NHTS Variability Estimate to MN Detailed Data

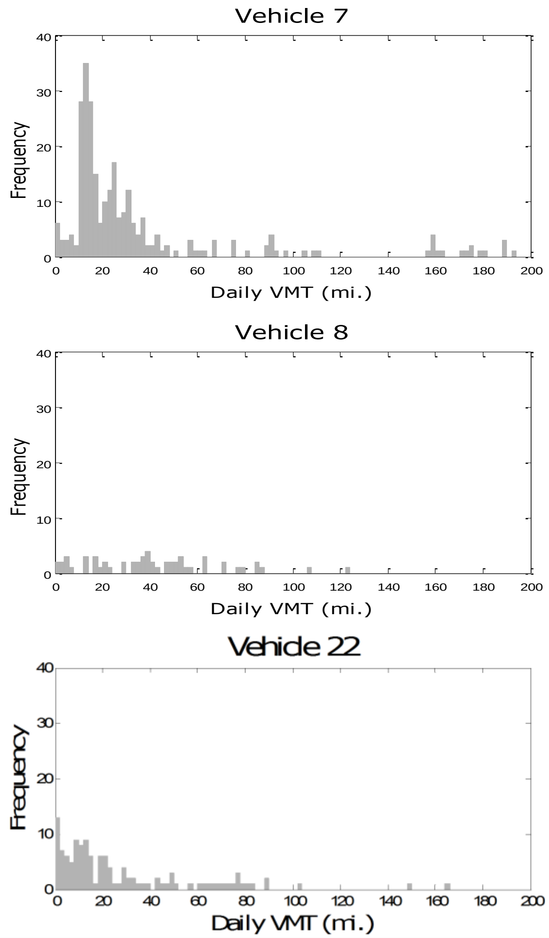
- Additionally, the MN detailed data displays the expected trend:



Variability Represented as a Family of Distributions

- To take advantage of the national representativeness of NHTS and the detail of the Minnesota data, we went forward using
  - NHTS average daily VMT to model variability across vehicles
  - Minnesota data to model variability across days
- To obtain a convenient closed-form CDF for the variability in VMT across days for each vehicle, we used the linear fit to the means to fit a family of exponential distributions





Conclusions

- Since NHTS collects only one day of data per vehicle, estimating variability in VMT across days for each vehicle is problematic
- This method based on aggregating NHTS 2001 survey day distance by average VMT results in an unexpected and so far unexplained trend, indicating that it may be unreliable.
  - Other variability-related studies based on NHTS 2001 survey day data may be similarly biased towards shorter VMT
  - Another method has been posed by ORNL to estimate variability in VMT based on mean and mode of daily VMT, but it also requires commute distance and is therefore limited to commuter vehicles
  - This analysis has not yet been repeated with NHTS 2009, but BESTMILE would need to be used and might complicate it
- In future NHTS surveys, multiple days of trip data from each respondent would be valuable for improving estimates of VMT variability across days

The paper that uses this method to optimize GHG emissions is available from: http://www.cmu.edu/me/ddl/publications.html

Questions or comments?

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Appendix

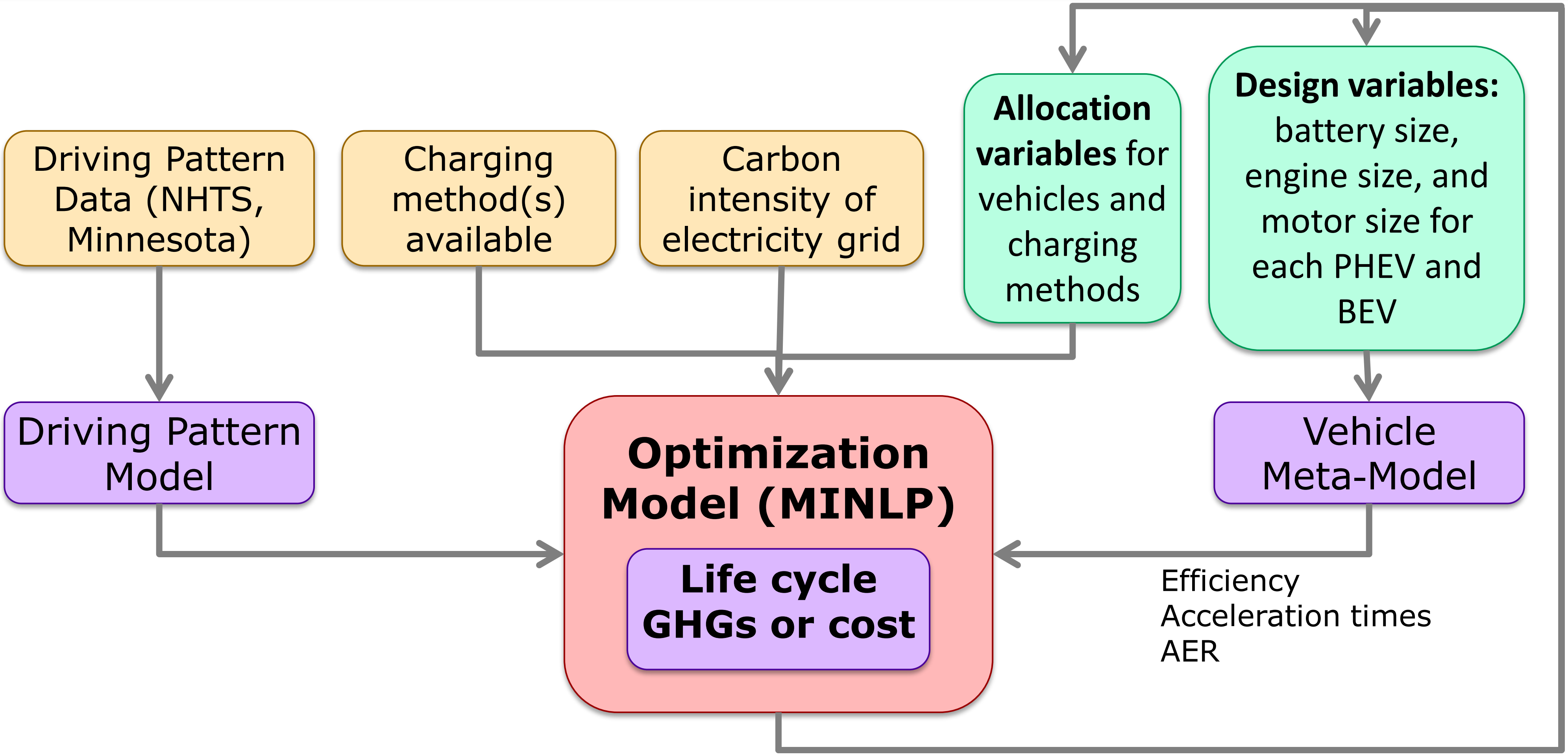
Relevant Data Available on Range

Data	Freely available?	Representative Sample?	Detailed driving distances over time for the same vehicle?
NHTS (trip distances, survey day driving distances, odometer readings, and “bestmile” estimates)	Yes	**Yes**	No
Detailed trip data for small numbers of personal vehicles	Sometimes	Maybe	**Yes**
Detailed trip data for small numbers of xEVs driven by early adopters	Sometimes	No	Yes

Driving Days Per Year

- Based on ratio of non-zero survey day driving distances for vehicles that have 2 valid odometer readings and both total and average distance <=200 miles: 249

Method: Data and Models



- Optimization model: minimize life cycle GHG emissions or cost over a fleet of vehicles by jointly determining
  1. Vehicle design (engine size, motor size, battery size, and battery swing window);
  2. Allocation of each vehicle design based on average annual VMT; and
  3. Allocation of home and workplace charging infrastructure

Research Questions

- Under the hypothetical scenario, we ask:
  1. What mix of vehicles minimizes GHG emissions? Cost?
  2. What is the GHG and/or cost reduction potential of dedicated workplace charging infrastructure?
  3. What effect does dedicated workplace charging have on optimal vehicle allocation and battery sizing for each objective?
  4. How similar are the GHG-minimizing and cost-minimizing scenarios?