UCR CE-CERT

# Machine Learning-based Mesoscopic Energy Consumption Models for Heavy-Duty Battery Electric Trucks

Emmanuel Hidalgo Gonzalez, Jacqueline Garrido, Kanok Boriboonsomsin, Matthew Barth

# Outline

- Background and Motivation
- Related work
- Methodology
  - modeling
  - Data processing
- Results
- Conclusion and future work

# Background and Motivation

1. Transportation sector in the United States has a crucial role in the economy

2. Transportation is the largest source of greenhouse gases and pollutants

3. Focus on ground transportation because it is the cheapest compared to air and sea transportation

UCR CE-CERT

# Background and Motivation

Adoption of electric vehicles can address the pollution issue:

1. Charged through renewable sources
2. Efficiency
3. Lower maintenance

Electric vehicles have become more common on the roads, but electric heavy-duty trucks are falling behind. Some reasons are:

1. Shorter driving range than diesel trucks
2. Longer time to refuel
3. Driver anxiety

There is a need to understand how these battery electric trucks (BETs) work to address the issues.

UCR | CE-CERT

# Related Work

Wang *et al.* (2019) proposed to simulate the power of BETs using real-world data from different diesel-powered trucks. The simulated data is then mapped into a map to create different links that fit a mesoscopic model. The mesoscopic model then uses multilinear regression to predict energy consumption.

Qi *et al.* (2017) estimated energy consumption using a decomposition of two impact factors: positive kinetic energy (PKE) and negative kinetic energy (NKE) for eco-routing models.

Holden *et al.* (2020) developed a model that estimates the energy consumption of different electric vehicles. At the same time, their software contains different training algorithms. Some of them are traditional linear regression.

# Modeling

Modeling energy consumption is essential to understand the behavior of BETs.

| Microscopic | Mesoscopic |
| --- | --- |
| Input is high resolution (1 Hz data) | Input can vary |
| Very accurate | Less accurate |
| Computationally Expensive | Faster to compute |
| Instantaneous data | Average data |

| Linear Regression | Random Forest |
| --- | --- |
| Fast to compute | Takes time depending on the dataset |
| Easy to understand | Black box approach |
| Complex data difficult to fit | Can fit complex data |

UCR CE-CERT

# Data Processing

Data Description:

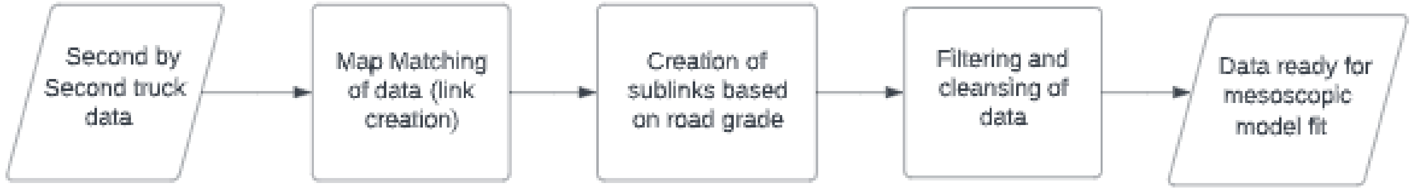
1. Real-world, in-use, operational data collected from different class 8 battery electric trucks in LA area

2. Collected using a combination of GPS and loggers at the frequency of 1 Hz

3. Collected data was for a period of 1-6 months

4. The real-world data was used to create a simulated BET dataset.

Flow of processing:




UCR CE-CERT

# Data Processing

Simulation of BET

The main reason for creating simulated data is to compare it against real-world data.

Simulated data allows the introduction of more variables. In this case, mass is of particular interest.

The simulation allowed to obtain data at different weights.

Main equation for simulation:

$$\boldsymbol{W_{tract}} = \boldsymbol{m} \cdot \boldsymbol{v} \cdot a + \frac{\mathbf{1}}{\mathbf{2}}\rho \cdot \boldsymbol{C_d} \cdot \boldsymbol{A_f} \cdot \boldsymbol{v^3} + \boldsymbol{m} \cdot \boldsymbol{g} \cdot \boldsymbol{C_{rr}} \cdot \boldsymbol{v} \cdot \mathbf{cos}\,\boldsymbol{\theta} + \boldsymbol{m} \cdot \boldsymbol{g} \cdot \boldsymbol{v} \cdot \mathbf{sin}\,\boldsymbol{\theta}$$

Where m is BET mass, v is instantaneous speed, a is instantaneous acceleration, ρ is air density, $C_d$ is coefficient of drag, $A$ is BET front area, $C_{rr}$ is coefficient of rolling resistance of BET tires, $g$ is gravity, $\theta$ is the angle of inclination of the road (road grade).

# Data Processing

Machine learning algorithm used: Random forest.

Random forest regressor is a supervised machine learning algorithm that builds decision trees on subsets of the data. This allows to create many trees and create a “forest” of random samples. The algorithm then takes an average of the samples to make a decision. The random forest regressor has been shown to have better results than the linear regressor.

Input: link level average speed (mph), link road grade, weight (for simulated data only)
Output: link level energy consumption in kWh/mile

After hyperparameter tunning:

- Number of trees: 200
- Depth: 15

UCR CE-CERT

# Results

| Data | R2 score using random forest | R2 score using linear regression |
|---|---|---|
| Real-world electric truck | 0.52 | 0.21 |
| Simulated BET without weight | 0.79 | 0.23 |
| Simulated BET with weight | 0.89 | 0.28 |

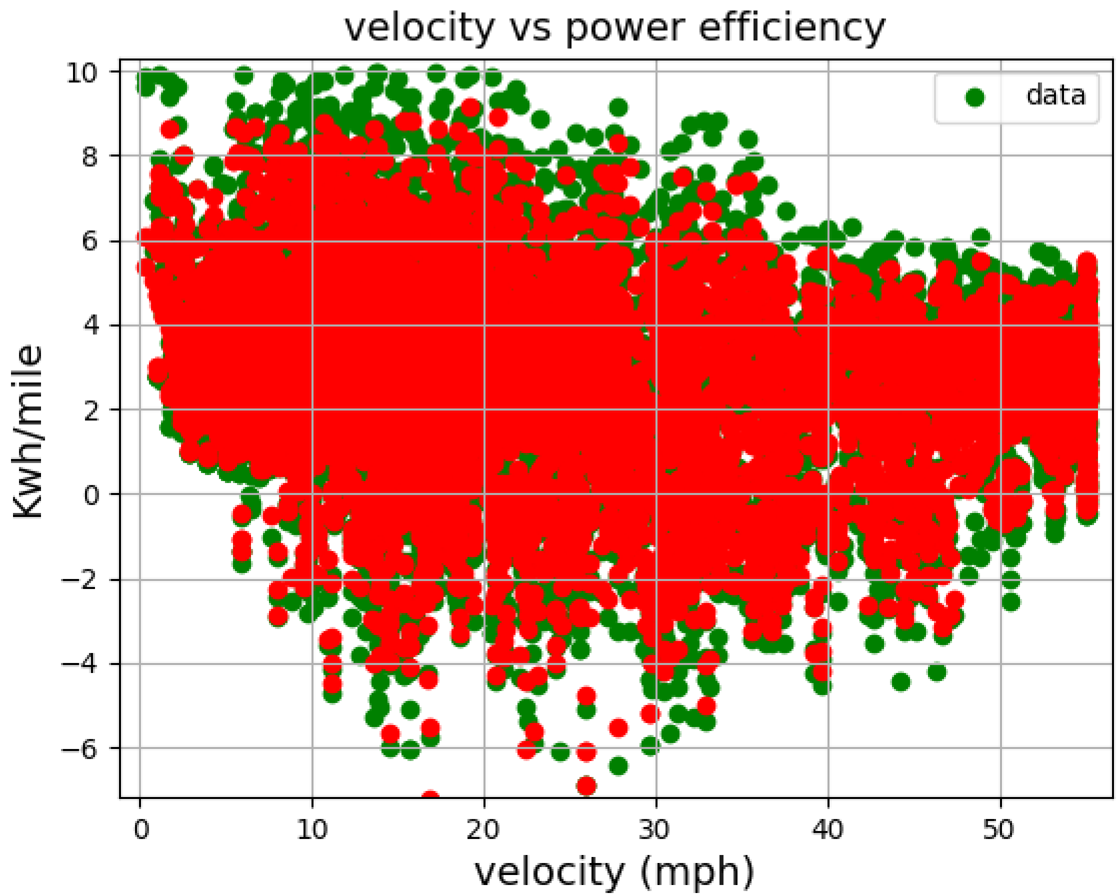
Summing up the energy consumed of the real-world electric truck and dividing by the distance traveled yields an efficiency of 1.81 kWh/mile

Simulated BET without weight efficiency: 1.83 kWh/mile

Simulated BET with weight efficiency: 1.90 kWh/mile

# Results

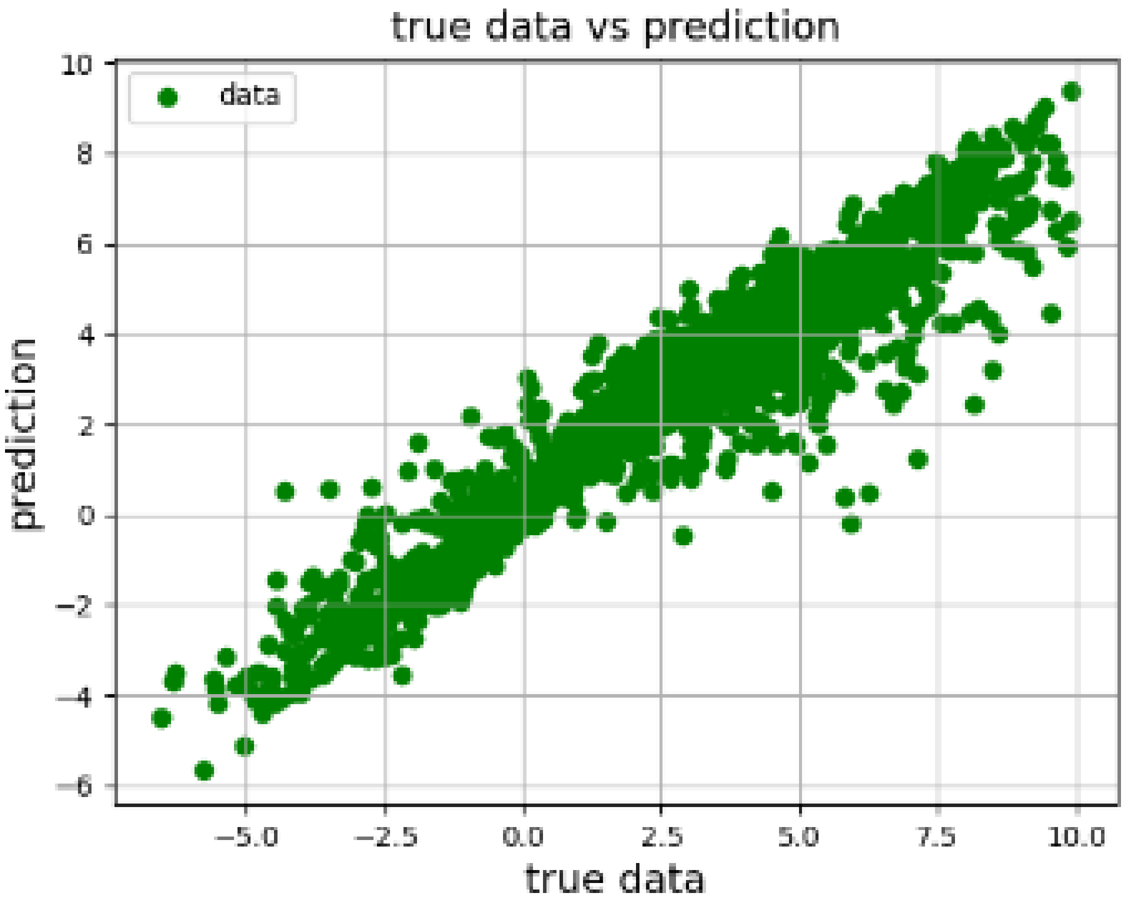
Simulated BET with weight:




Green dots represent the link-level velocity vs. power efficiency from the data
Red dots represent the prediction from random forest

# Results

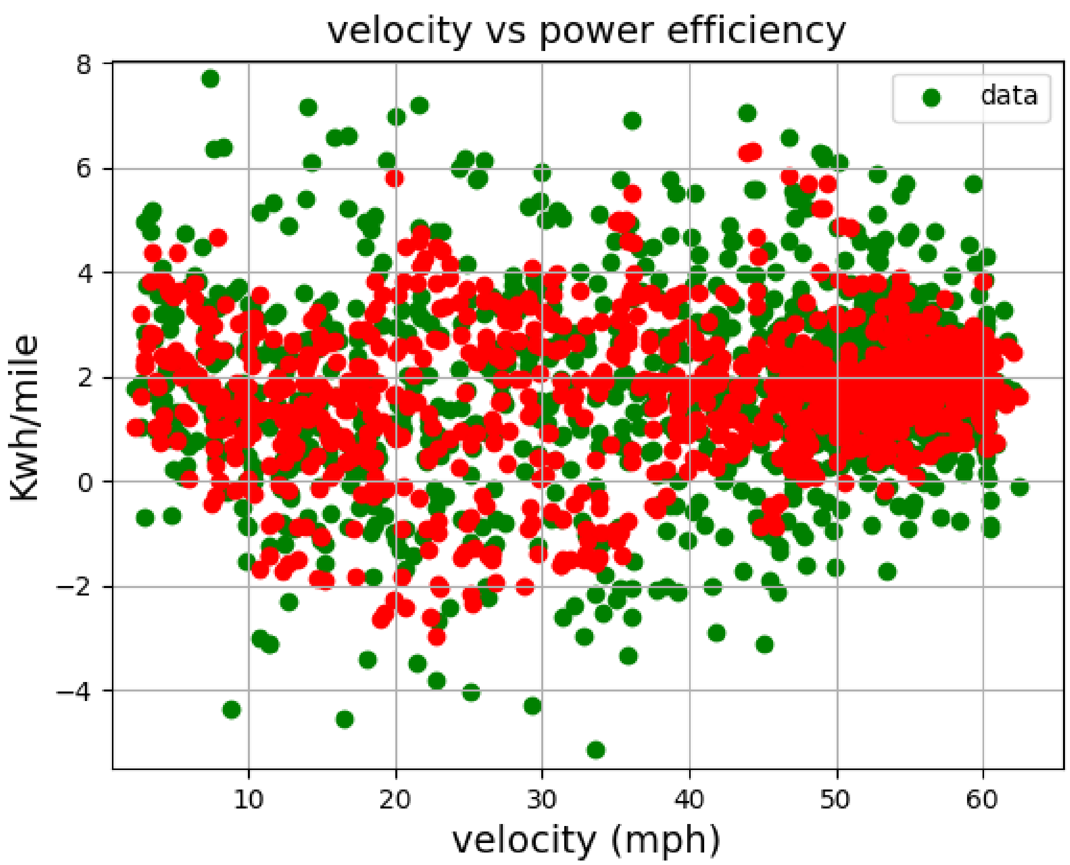
Simulated BET with weight:




Each dot represents the energy consumption (in kWh/mile) of the simulated data vs the prediction of random forest regressor

# Results

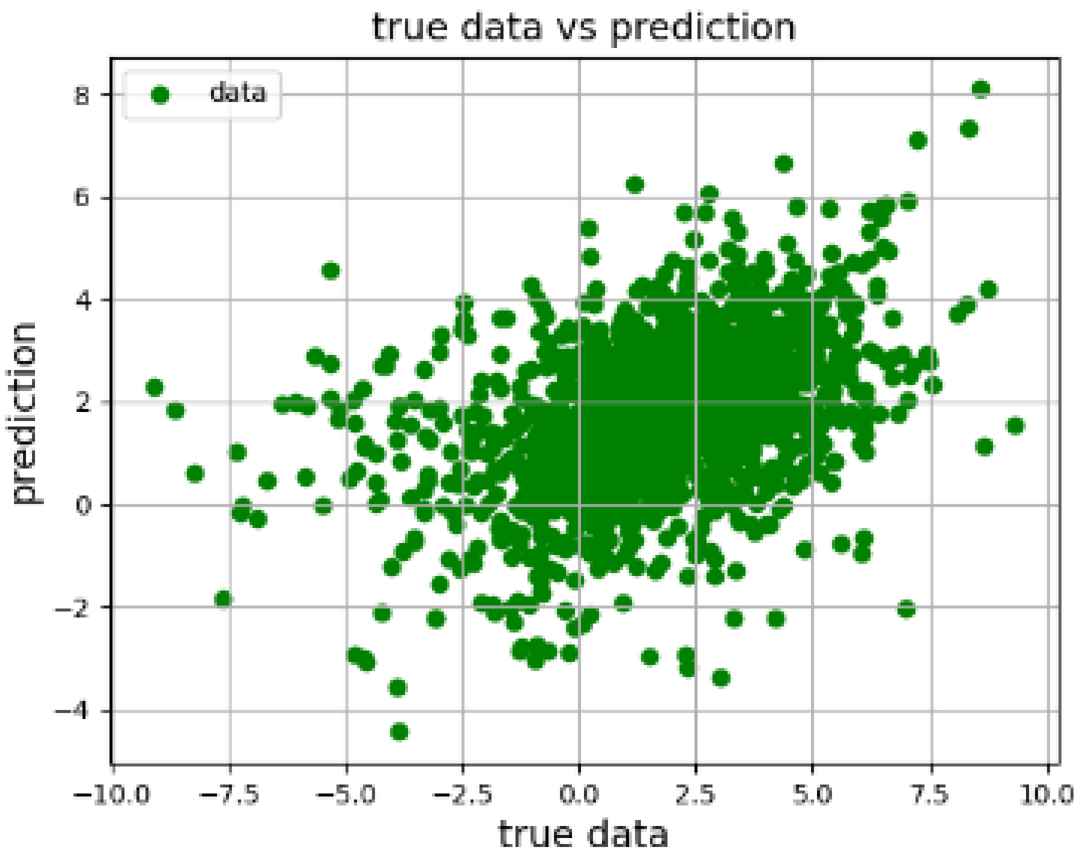
Real-world electric truck:




Green dots represent the link-level velocity vs. power efficiency from the data
Red dots represent the prediction from random forest

# Results

Simulated BET with weight:




Each dot represents the energy consumption (in kWh/mile) of the simulated data vs the prediction of random forest regressor

# Conclusion and Future Work

- Understanding the energy consumption of BETs is necessary to be able to optimize their operations
- Microscopic models are more accurate but require detailed data inputs, which may be expensive to obtain
- We proposed a mesoscopic model to estimate the energy consumption of BETs using the random forest regressor
- Mass is an important feature to have in these models
- For future work, we are working to develop an energy consumption model using real-world data but with the inclusion of weight.
- Implement the model in applications such as eco-routing

UCR CE-CERT