Project ID: ti100

High-Dimensional Data-Driven Energy Optimization for Multi-Modal Transit Agencies

Chattanooga Area Regional Transportation Authority

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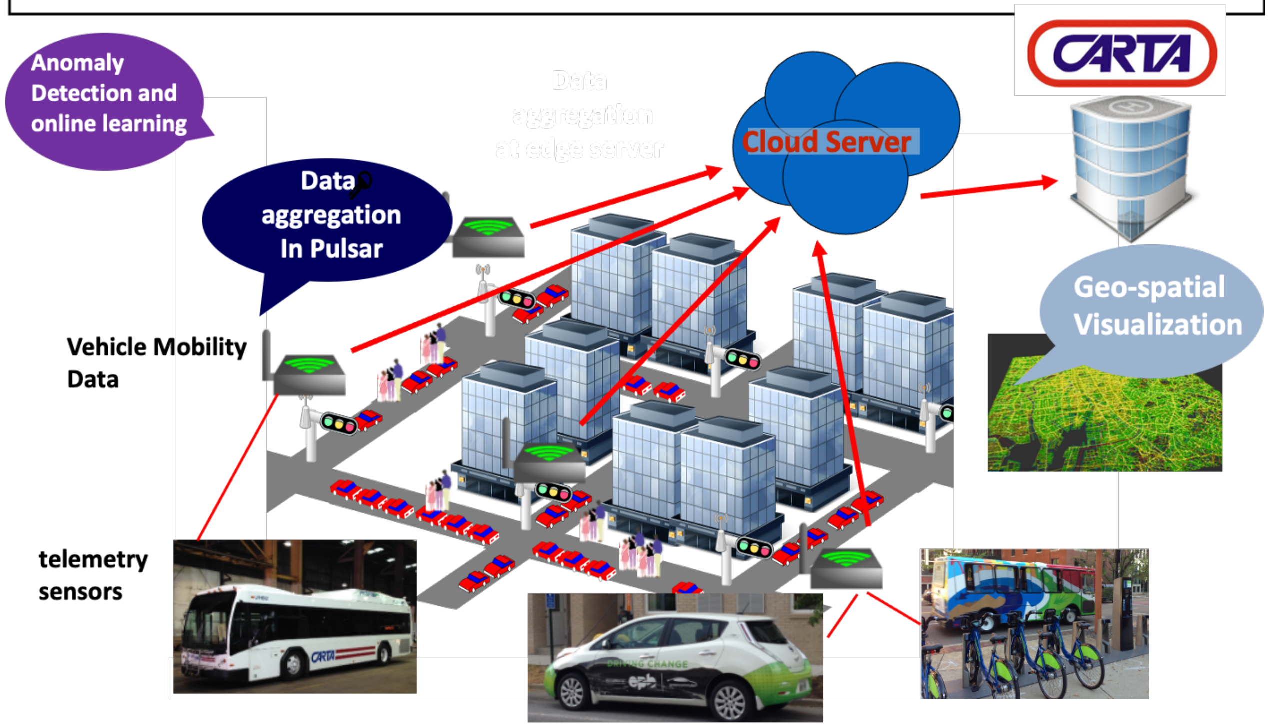
Background

This project is building a **high-resolution system-level data capture** and analysis for transit operations to provide CARTA the capability to **identify energy bottlenecks** and accurately **predict energy costs** of all operations.

The captured datasets contain real-time transit information about engine idling status, engine temperature, engine speed, throttle, vehicle speed fuel level, engine temperature, and road gradient.

Approach

High resolution sensor data aggregation from all transit vehicles.
Anomaly detection and data store for supporting high integrity, velocity, and volume
Micro (Vehicle Specific), Macro (Elevation, Weather and Traffic) Energy Prediction for Mixed Fleet
Operational Guidance for Mixed Fleet Operations and City-wide geo-spatial visualization.

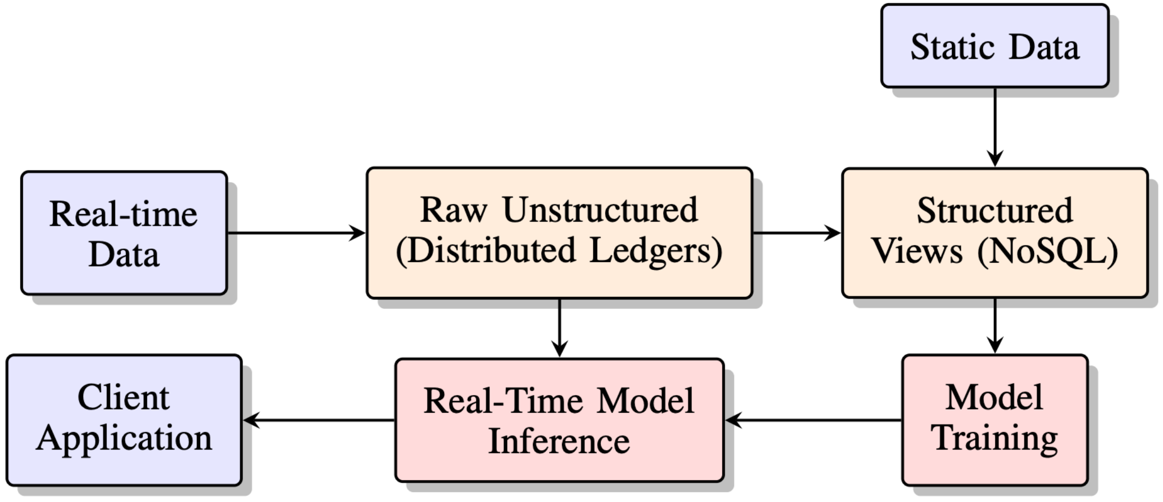


System Architecture

Source code: github.com/hdemma

Data Sources

- Data Aggregated since August 2019 to data store
- Analysis requires joining data from multiple real-time and static sources
- Future work: integration with Spark for real-time data synthesis
- Example: fuel consumption from ViriCiti + vehicle location from Clever Devices + weather from DarkSky + traffic conditions from HERE



The volume of data was so large that we had to design a distributed datastore

Any proposed future work is subject to change based on funding levels.

The Data Store Challenge and Approach

ISIS OpenStack

HERE

Viriciti

Weather

Clever

Pulsar Cluster

Brokers & Bookies – 5 Nodes

- 2 VPUs
- 8 GB Ram
- 40 GiB Root Disk
- 128 GiB Volume

Zookeeper – 5 Nodes

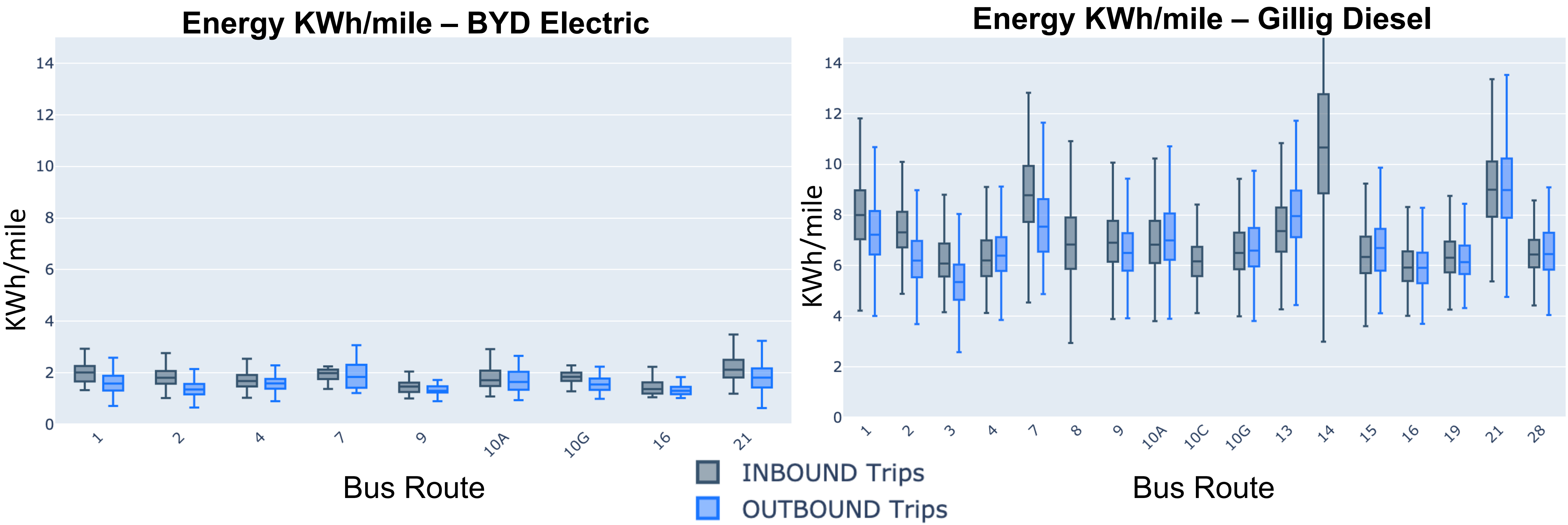
- 1 VPUs
- 8 GB Ram
- 40 GiB Root Disk
- 64 GiB Volume

MongoDB – Replica Set

- 2 storage nodes
  - 8 VPUs
  - 16 GB Ram
  - 150 GiB Root Disk
  - 4 TB Volume
- 1 arbitrator
  - 1 VPU
  - 2 GB Ram
  - 40 GiB Root Disk

- Features of the architecture
  - Distributed storage
  - Replicated Data
  - Real-time stream processing
  - Spatial queries
  - Integrated visualization
  - Temporal queries
  - Integrated joins for analysis across different data features
    - Weather
    - Traffic
    - Vehicle Telemetery

Analysis and Insights

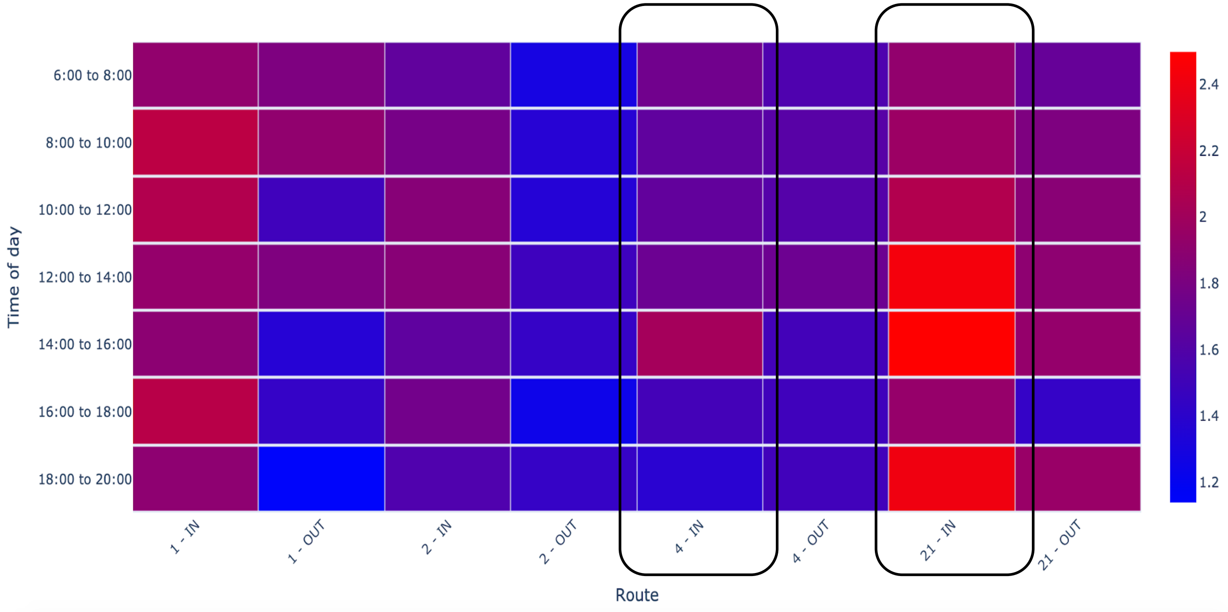


- The boxplots show the variation in KWh per mile for all trips on each route. (acknowledge the conversion.)
- Data range from December 20, 2019 to April 15, 2020
- KWh per mile is higher for Diesel vehicles compared to Electric vehicles. Also there is some variation between routes that implies electric vehicles (agencies have limited numbers) can be deployed strategically to lower the overall energy consumption
- Future Work: we are analyzing the differences between vehicle models and years.

Any proposed future work is subject to change based on funding levels.

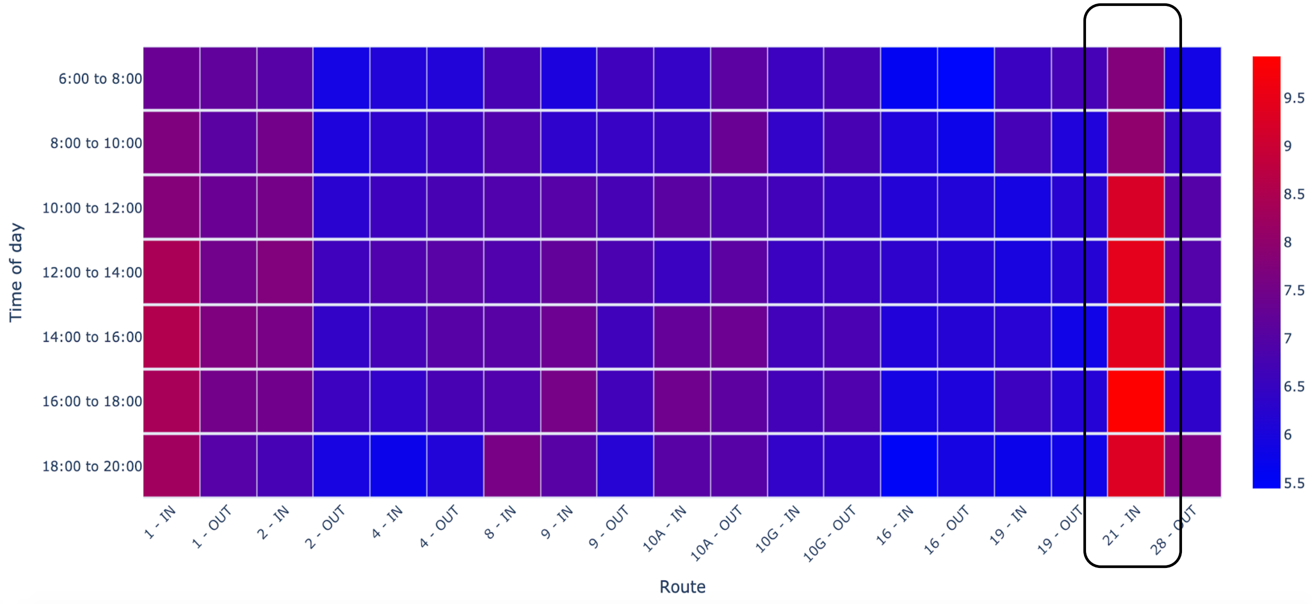
Analysis and Insights

Energy (kWh/mile) per Route – BYD Electric Vehicles



Route 21 – has more stops and hilly terrain

Energy (kWh/mile) per Route Gillig Diesel Vehicles

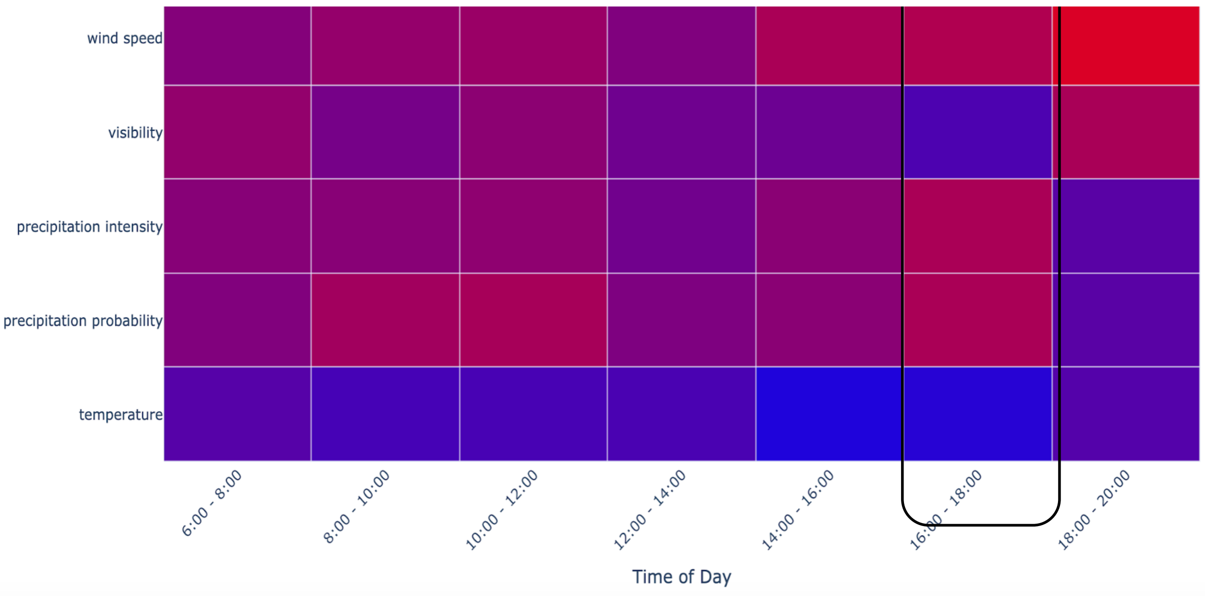


Route 21 – consumption is ~ 4 times more than electric

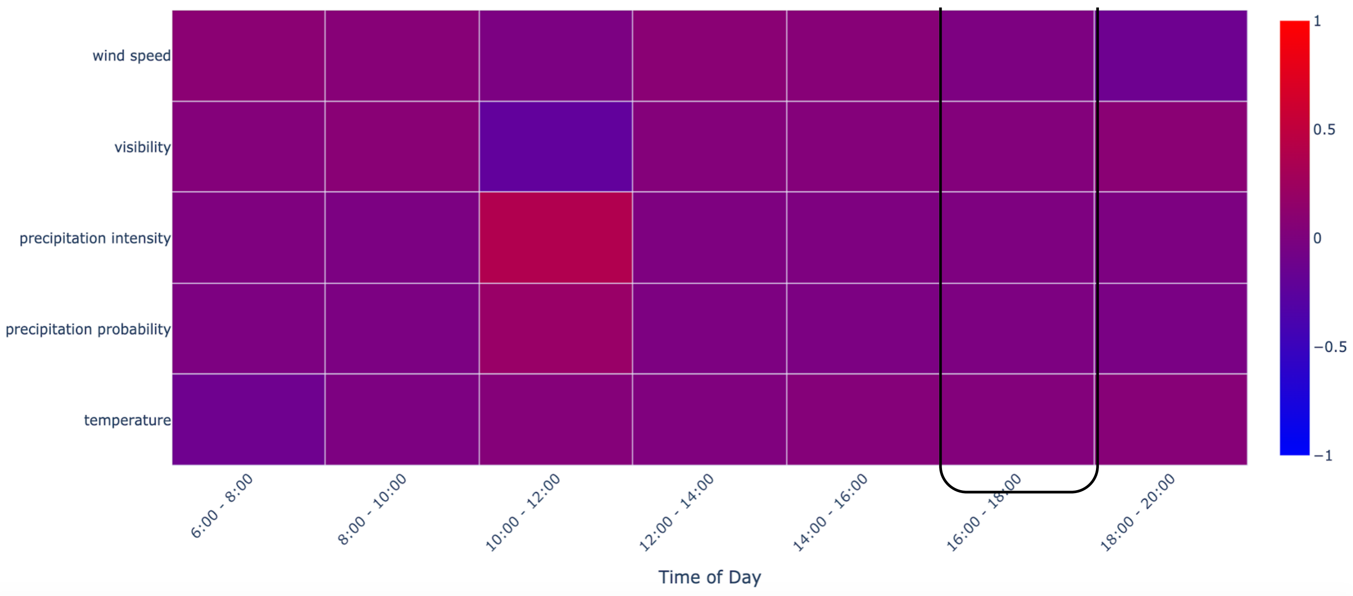
- Diesel vehicles are more affected by time of day than electric vehicles.
  This supports our thoughts that electric vehicles perform better in high traffic.
- The scales of the heatmap are different because of the difference in energy consumption magnitude between electric and diesel vehicles

Analysis and Insights

Weather – Energy Cost Correlation Matrix BYD Electric Vehicles (Route 4 Inbound)



Weather – Energy Cost Correlation Matrix Gillig Diesel Vehicles (Route 4 Inbound)

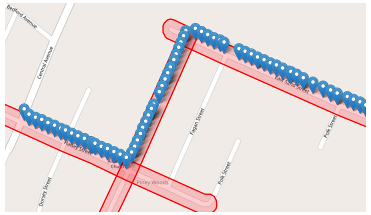


Electrics are much more sensitive to weather.

- Temperature has a high negative correlation with energy cost for Electric Vehicles (as temperature goes up, energy cost goes down).
- Weather affects electric and diesel vehicles very differently and hence it is important identify correlation between features for each fleet separately.
- Similarly, elevation affects the vehicles differently.
- We utilize this sensitivity in planning the assignment problem

Macroscopic Energy Prediction

- Motivation: **minimize the energy use of transit services** through routing, scheduling, and vehicle assignment.
- Prerequisite: **predict how much energy a transit vehicle will use** on a route at a time.



Vehicle make and model

Route (series of locations)

Day of week, time of day

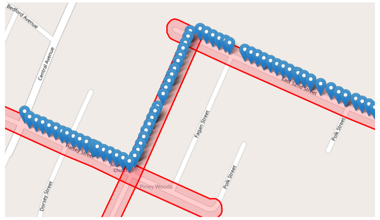
Expected Weather, Expected Traffic

→ Predictor → **Energy use** (gallons or Watt-seconds)

Contrast to micro prediction: we can rely only on features that are vehicle agnostic.

Macroscopic Energy Prediction Workflow

Noisy GPS data



Clean GPS data

Data from ViriCiti

electric, diesel, and hybrid vehicles (timestamps, GPS location traces, fuel levels / battery voltage and current)

Calculate Energy Consumption

consumption time series from using battery current and voltage or fuel levels

Map Locations to Roads

map noisy GPS location traces to road segments using intelligent filtering and OSM

Generate Samples

segment time series into disjoint contiguous samples based on road segments

Augment Samples with Additional Data

for each sample, add elevation change, traffic, and weather features

Create Training and Test Sets

for each vehicle model, create randomized training and test sets

Machine Learning Models

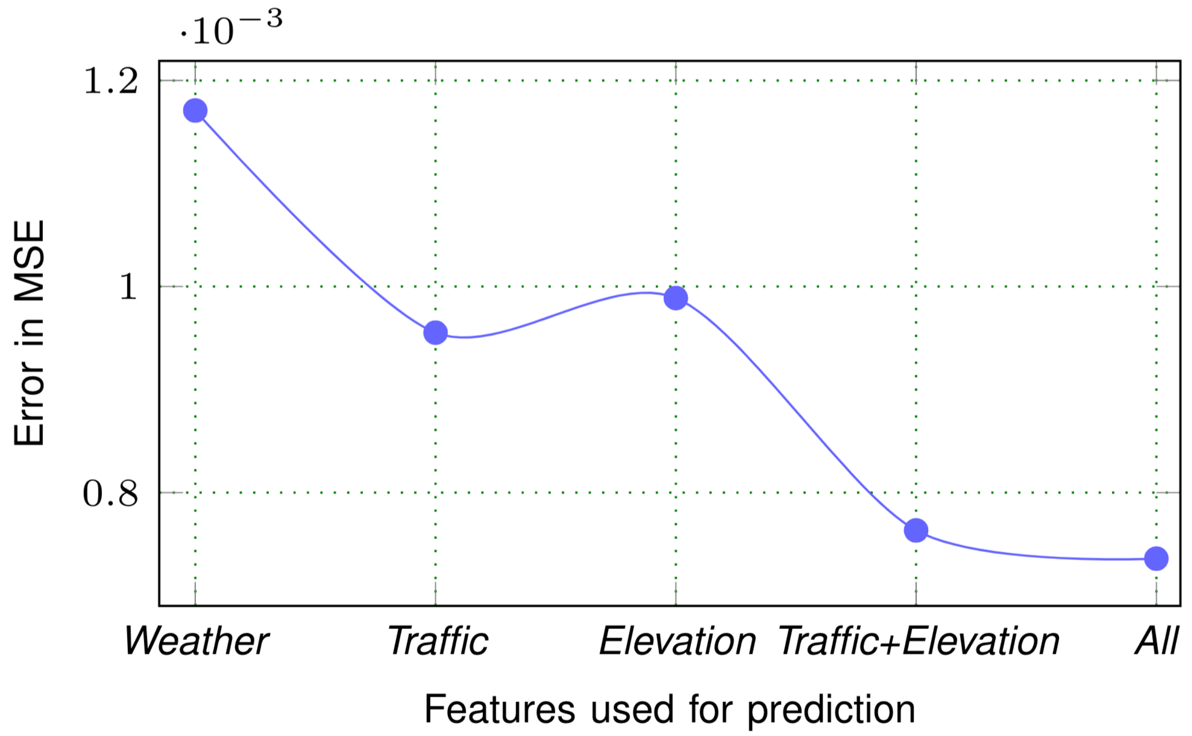
apply linear regression, decision tree, deep neural networks

Training, Evaluation, Prediction

Macroscopic Energy Prediction Results #1

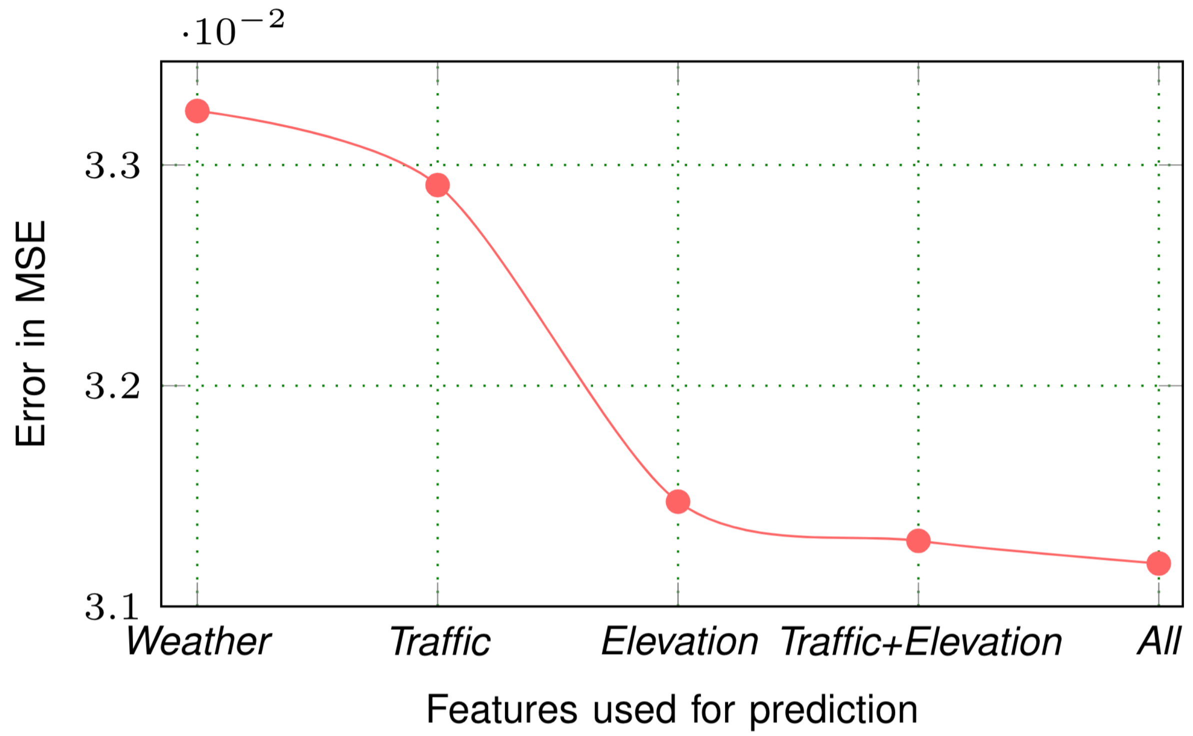
Which data features are most useful for prediction?

Diesel (2014 Gillig Phantom)



Both elevation and traffic data are significant for Diesel vehicles

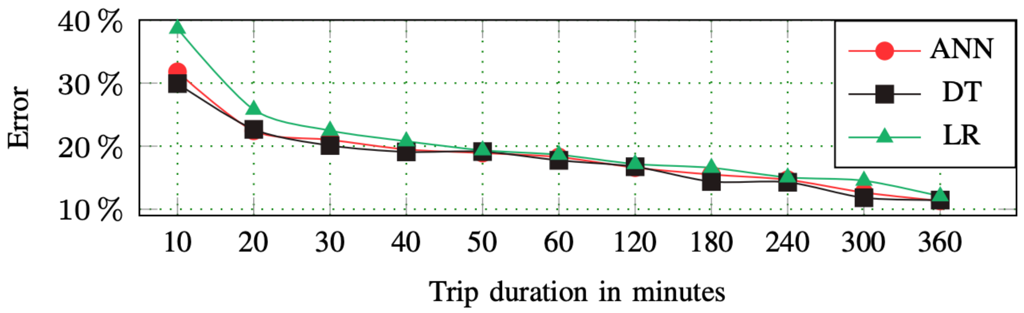
Electric (2016 BYD K9S)



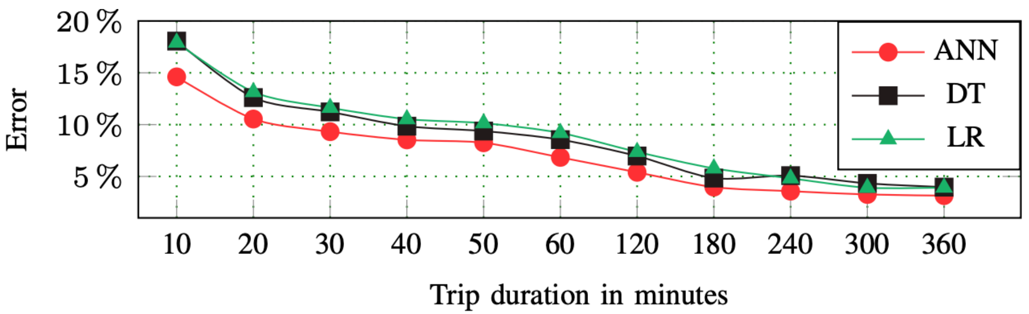
Elevation is by far the most significant feature for electric vehicles

Macroscopic Energy Prediction Results #2

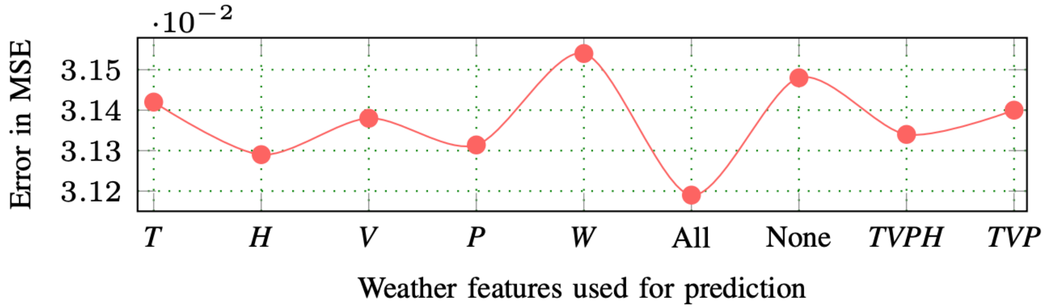
Electric

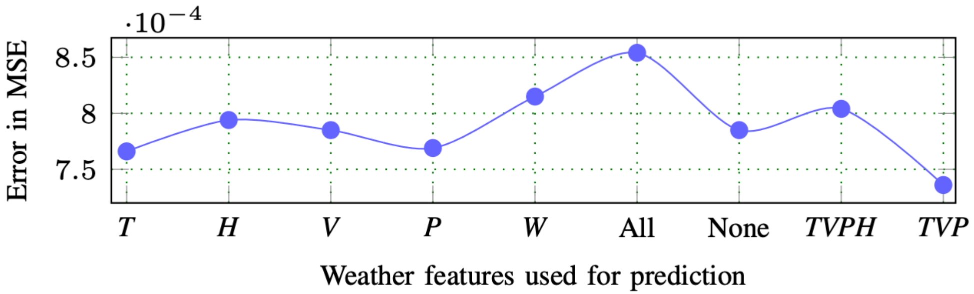


Diesel



Prediction error for longer trips with neural network (ANN), decision tree (DT), and linear regression (LR).





Prediction error with various weather features: temperature (T), humidity (H), visibility (V), wind speed (W), and precipitation (P)

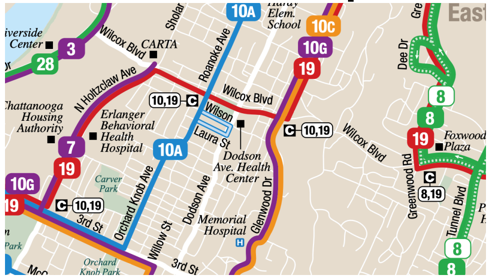
For electric vehicles, we attain lowest error when we use all five features together

For diesel vehicles we attain lowest error using only three features: temperature, visibility and pressure (need investigation)

Vehicle Assignment and Charging Optimization

- <u>Motivation</u>: **minimize the energy use of transit services** through vehicle assignment and electric charge scheduling
- Problem:

Transit trips



assign

Vehicles (ICEV and EV)

schedule (for Evs)

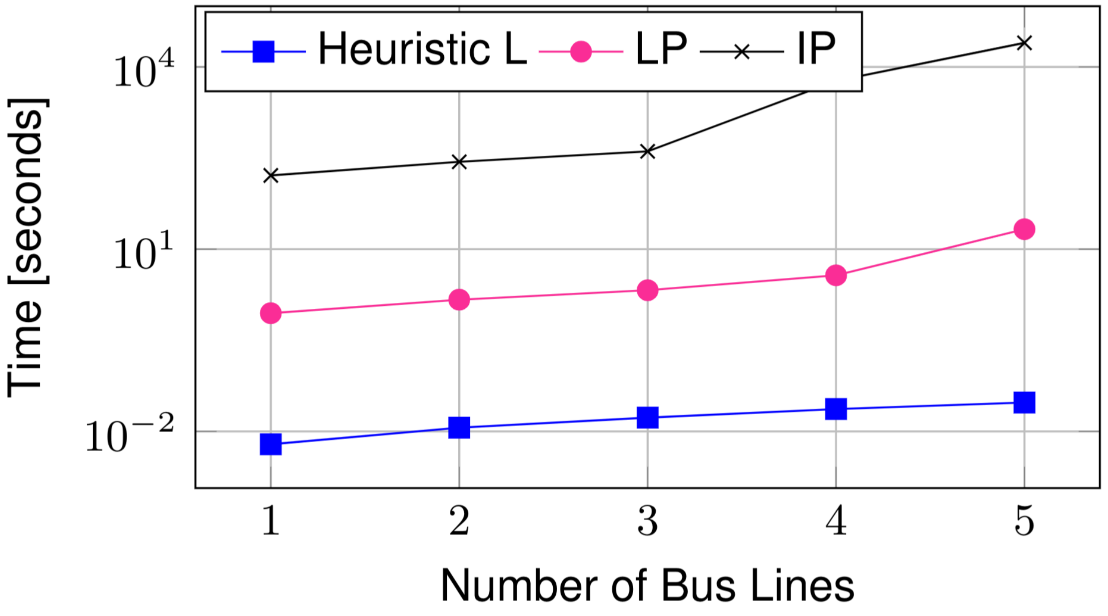
Charging

- Computational approaches (ongoing work)
  - **Integer program**: finds optimal solution, but does not scale well computationally
  - **Custom heuristics** (L and B variant): very efficient computationally
  - **Genetic algorithm**: computationally efficient, improves custom heuristics with random search

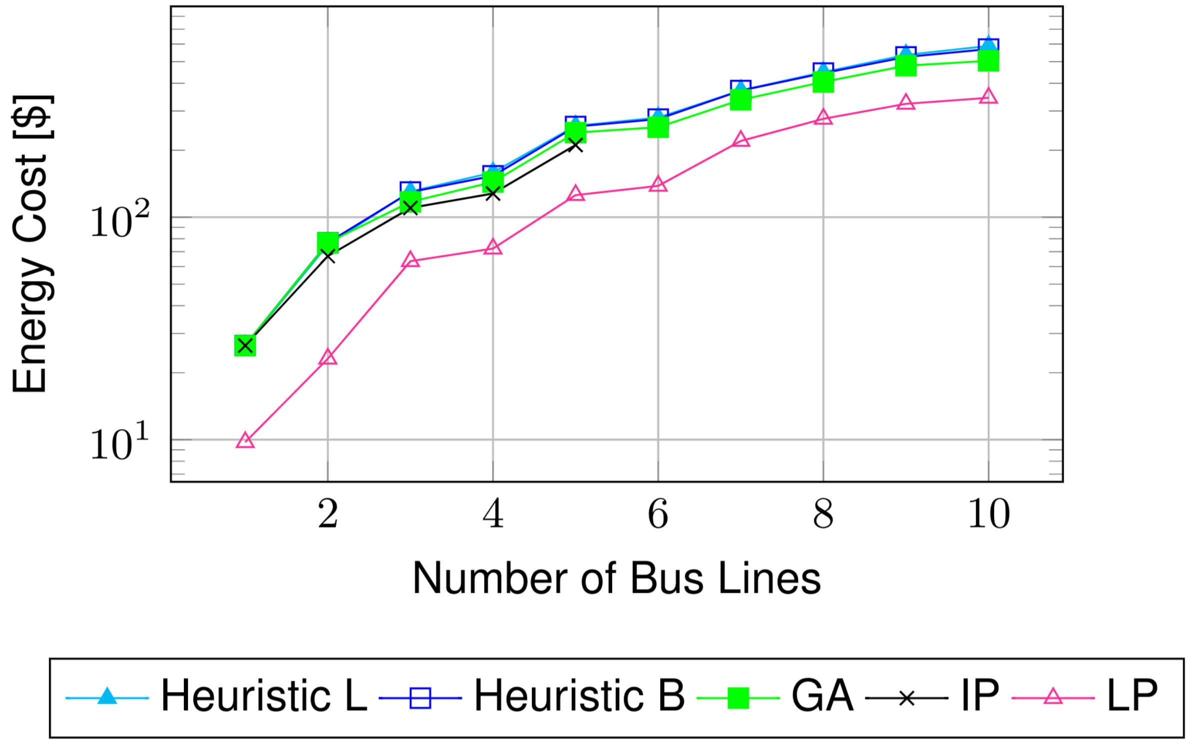
Preliminary Optimization Results

How do the proposed algorithms perform?

Computational Complexity

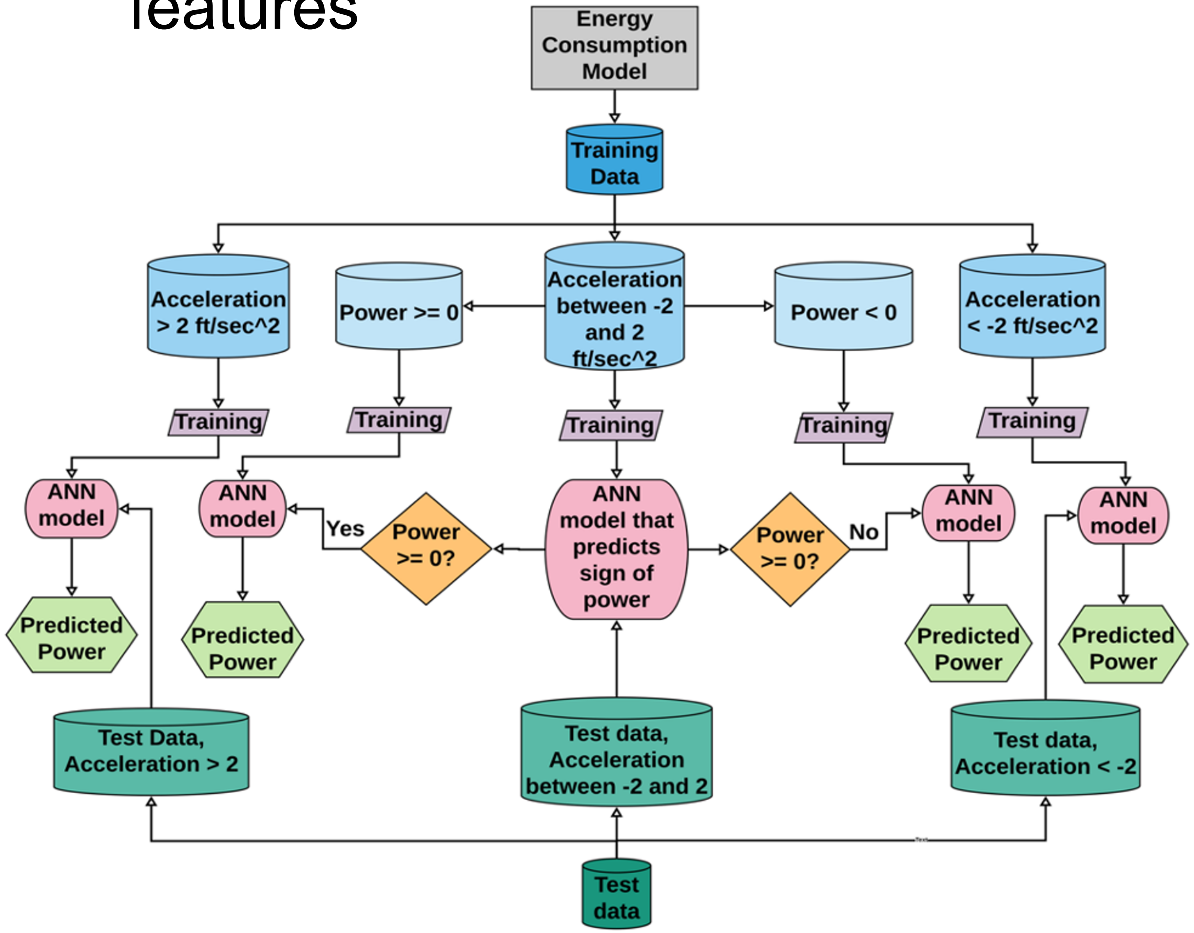


Energy Cost

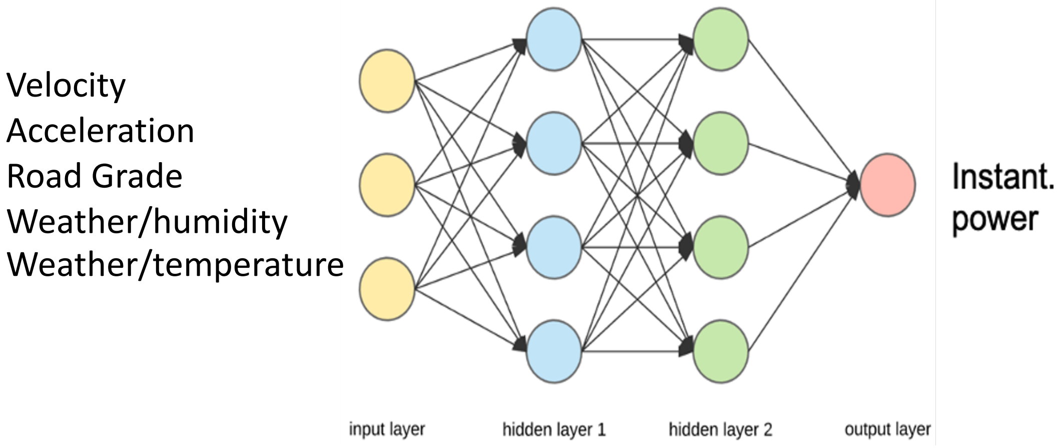


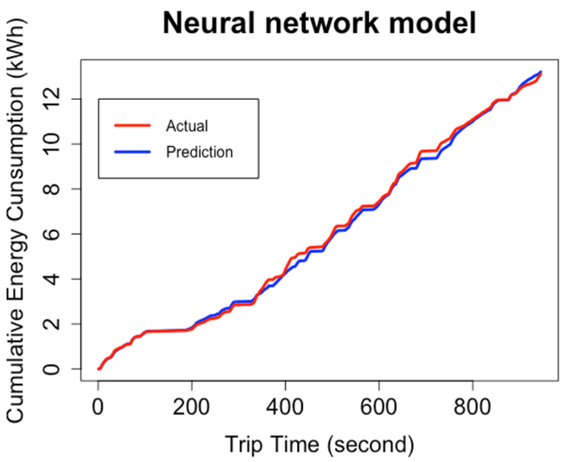
Microscopic Energy Prediction Model

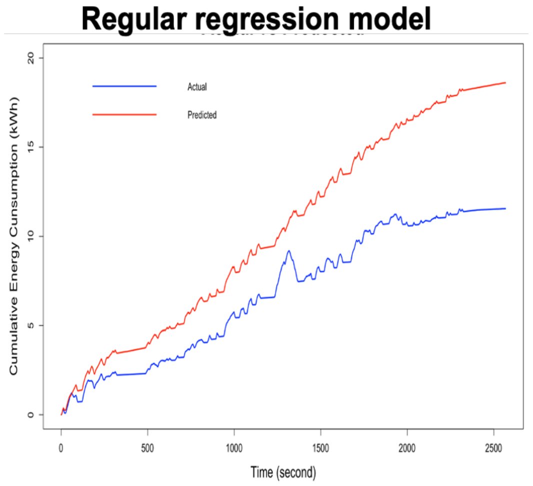
Classifying data based on driving features



Variable and model selections for optimal prediction performance





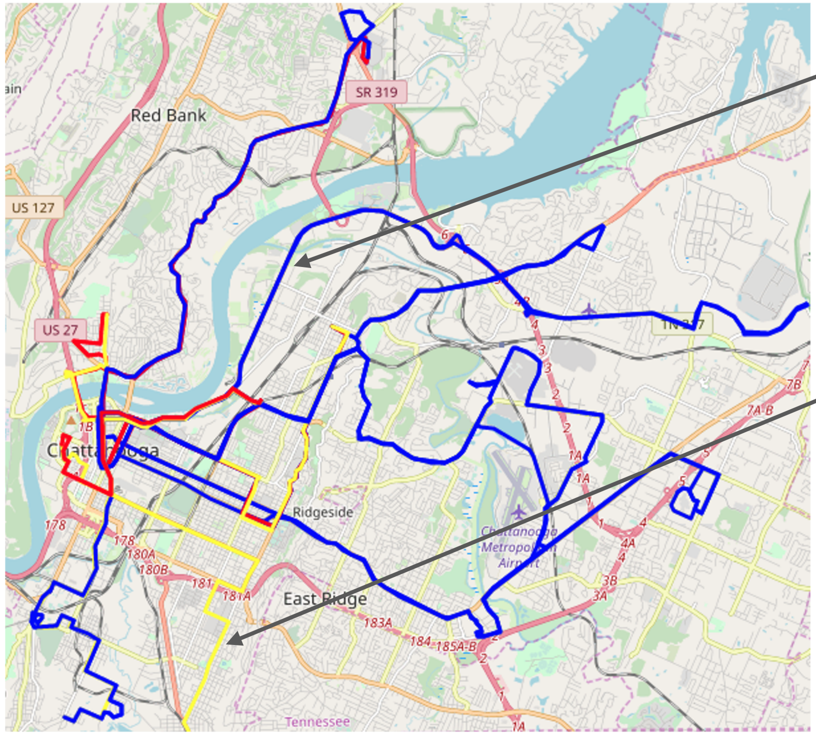


Visualization Framework for Operational Guidance

- Historical trends and real-time monitoring
- Technologies:
    - HoloVIZ - server and dashboard framework, jupyter notebook integration
    - deck.gl, vis.gl, kepler.gl - visualization engine from Uber Technologies
- Accessible by Jupyter notebook and web client

Visualization: Historical Trends

Energy consumption depends on route as well as time of day



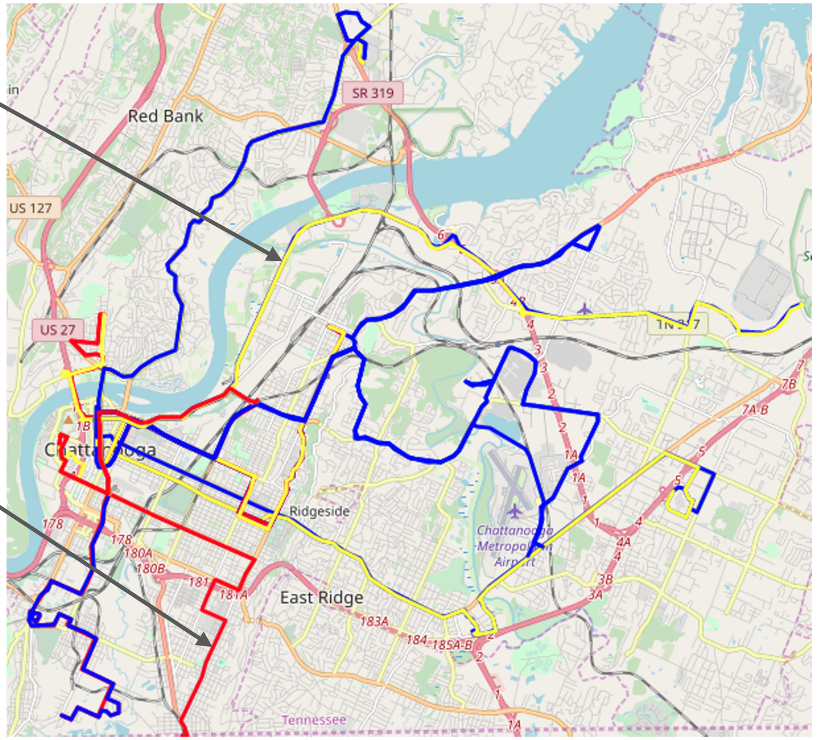
6AM to 9AM

Legend: Energy Usage (Per Quantile)

Light (Q1 and Q2)

Moderate-Heavy (Q3)

Heavy (Q4)



3PM to 6PM

PUBLICATIONS

- Poster at 2019 Tennessee Sustainable Transportation Forum & Expo
- Data-Driven Prediction of Route-Level Energy Use for Mixed-Vehicle Transit Fleets, accepted at SmartComp 2020. Preprint available at https://arxiv.org/abs/2004.06043
- Deep-Edge: An Efficient Framework for Deep Learning Model Update on Heterogeneous Edge, accepted at ICFEC 2020. Preprint available at https://arxiv.org/abs/2004.05740
- Minimizing Energy Use of Mixed-Fleet Public Transit for Fixed-Route Service. Submitted to IJCAI 2020. Preprint available at https://arxiv.org/abs/2004.05146
- Energy, electrification and evaluation: Data driven public transit. Presentation invited at 17th Transportation Research Board Tools of the Trade conference.
- A Review and Outlook of Energy Consumption Estimation Models for Electric Vehicles. Submitted to Renewable & Sustainable Energy Reviews. Preprint available at https://arxiv.org/abs/2003.12873

Summary

Relevance

Reduce energy consumption of public transit fleet through vehicle optimization.

Approach

Collaborative partnership with transit agency operating mixed-vehicle fleet.

Accomplishments

- Data collection completed.
- Prediction models developed.
- Ability to inform capital vehicle acquisition and deployment strategies.