Optimizing the Energy Usage of EV's and ICEV's in Public Transportation

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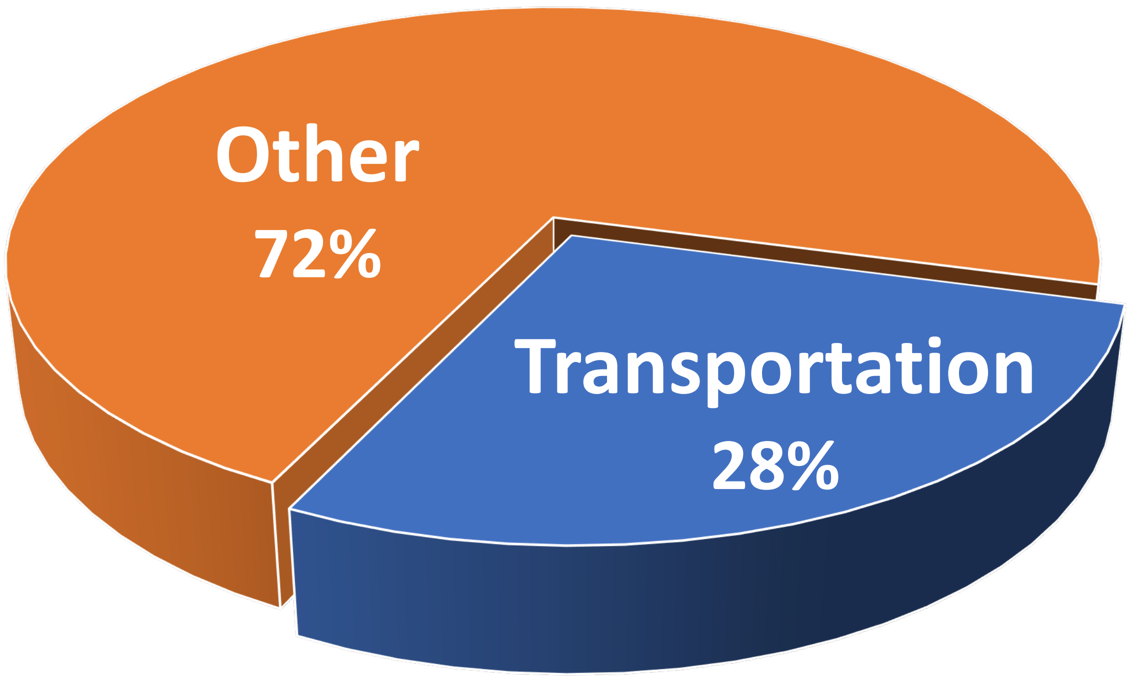
Transportation and Energy

Total energy used in the U.S. [1]



Annual CO_2 emission of buses in the U.S. [2]

19.7 million metric tons

[1] U.S. Energy Information Administration, *Monthly Energy Review*, Table 2.1, May 2020.

[2] Office of Transportation and Air Quality, "Fast facts: U.S. transportation sector greenhouse gas emissions 1990–2017," Tech. Rep. EPA-420-F-19-047, June 2019.

Electric Vehicles

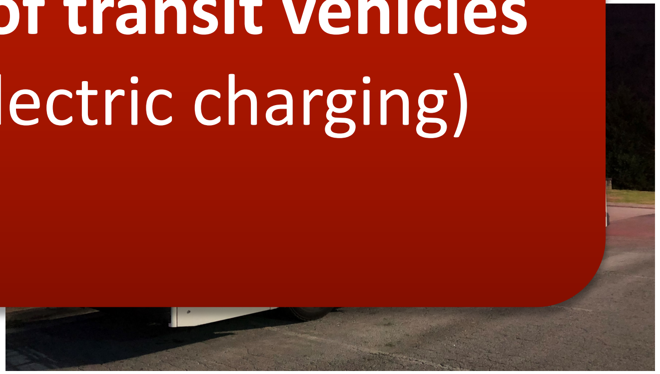
Cost of typical transit bus [3]

How to optimize the operation of a mixed fleet of transit vehicles
(e.g., assign vehicles to transit trips, schedule electric charging)
to minimize energy usage?

[3] A. O’Donovan, J. F. Analyst, and C. McKerracher, “Electric buses in cities: Driving towards cleaner air and lower CO2,” Bloomberg New Energy Finance, March 2018.

Mixed fleets of transit vehicles

Diesel



Hybrid

HD-EMMA: High-dimensional Data-driven Energy optimization for Multi-Modal transit Agencies

- Funded by the Department of Energy under Award DE-EE0008467 * (2019 – 2021)
- Project partners include

UNIVERSITY of HOUSTON

PI: **Aron Laszka**
https://aronlaszka.com/

VANDERBILT UNIVERSITY

PI: **Abhishek Dubey**
https://scopelab.ai/

UofSC South Carolina

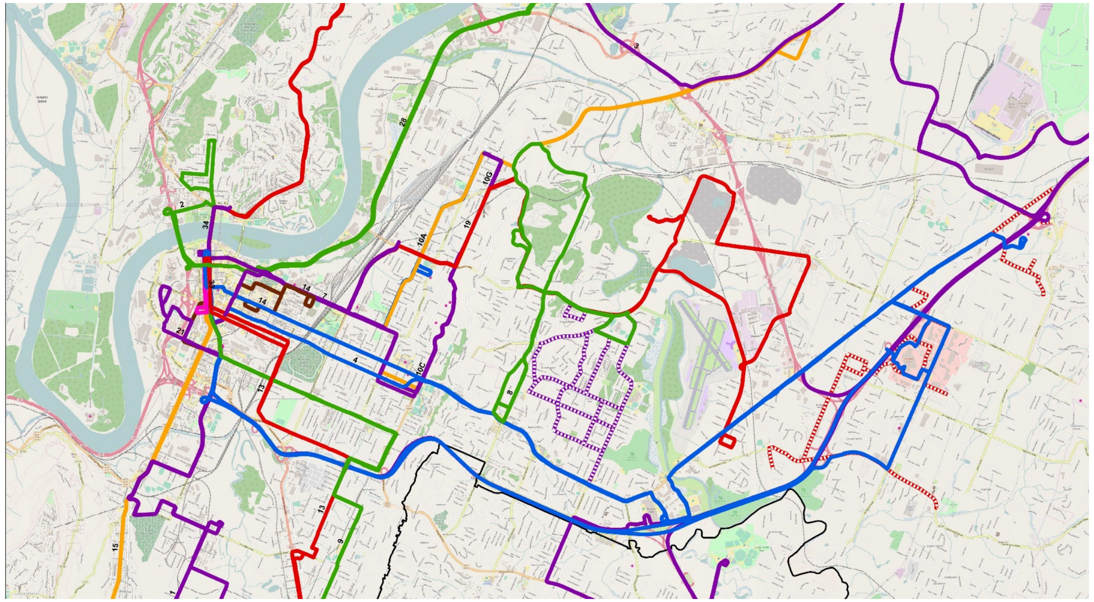
PI: **Yuche Chen**

- Project website: **https://smarttransit.ai/**

* This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

Chattanooga Area Regional Transportation Authority

- Project lead, PI: **Philip Pugliese** (Transportation System Planner)
- CARTA serves the Chattanooga, TN area, providing over 3 million passenger trips per year
- CARTA spends more than $1.1 million on fuel annually



- CARTA operates a mixed fleet of ICEVs, EVs, and hybrid vehicles

Presentation Outline

1. **Data collection, storage, and analytics**
2. **Macroscopic energy usage prediction**
3. **Transit optimization algorithms**
4. **Supporting results:**
   microscopic prediction and visualization
5. **Related transit projects**

1. Data Collection and Storage

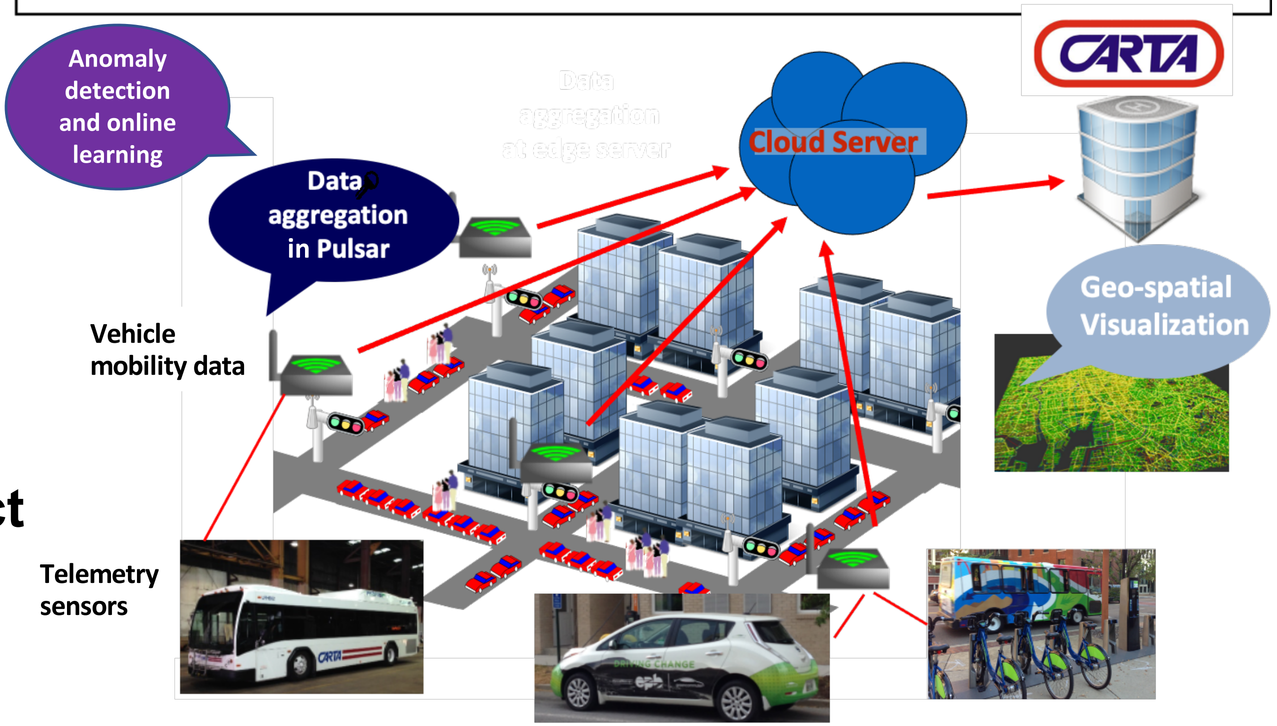
Background

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**, accurately **predict energy costs** of all operations, and to **optimize vehicle assignments** and **charging schedules**.

Source code and datasets:
`https://smarttransit.ai/energy.html`

Approach

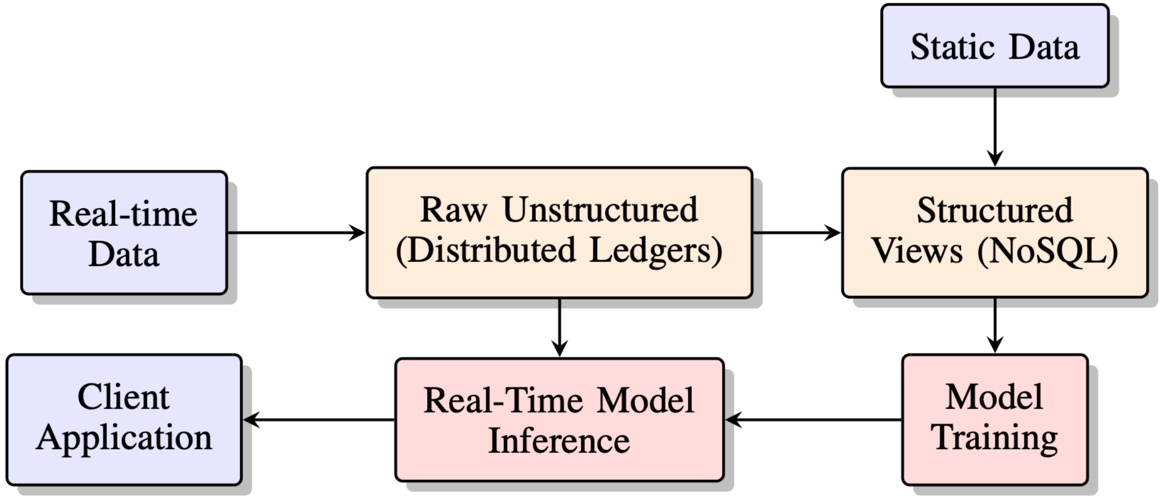
High resolution sensor data aggregation from all transit vehicles.
Anomaly detection and data store for supporting high integrity, velocity, and volume
Micro (Vehicle Specific), Macro (Elevation, Weather and Traffic) Energy Prediction for Mixed Fleet
Operational Guidance for Mixed Fleet Operations and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



System architecture

Data Sources

- Data aggregated since August 2019 into the 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



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

Data Store Approach

OpenStack

HERE

ViriCiti

Weather

Clever

Pulsar Cluster

Brokers & Bookies – 5 Nodes
- 2 VPUs
- 8 GB Ram
- 40 GiB Root Disk
- 128 GiB Volume

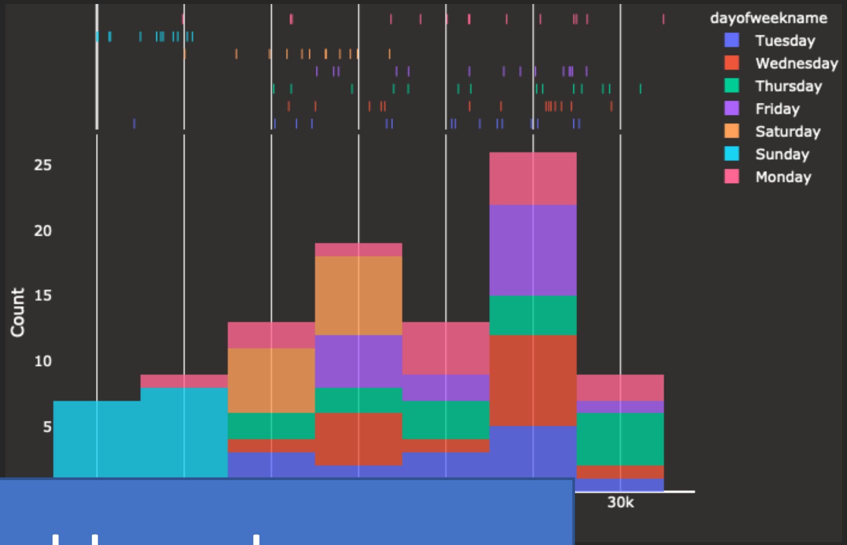
Zookeeper – 5 Nodes
- 1 VPUs
- 8 GB Ram
- 40 GiB Root Disk
- 64 GiB Volume

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 telemetry

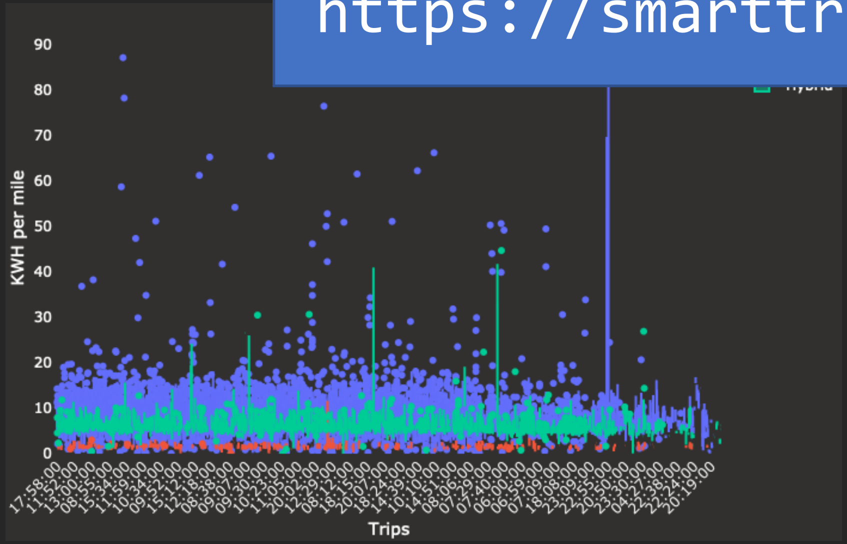
Energy Consumption Distribution by Fleet

Daily Energy Consumption

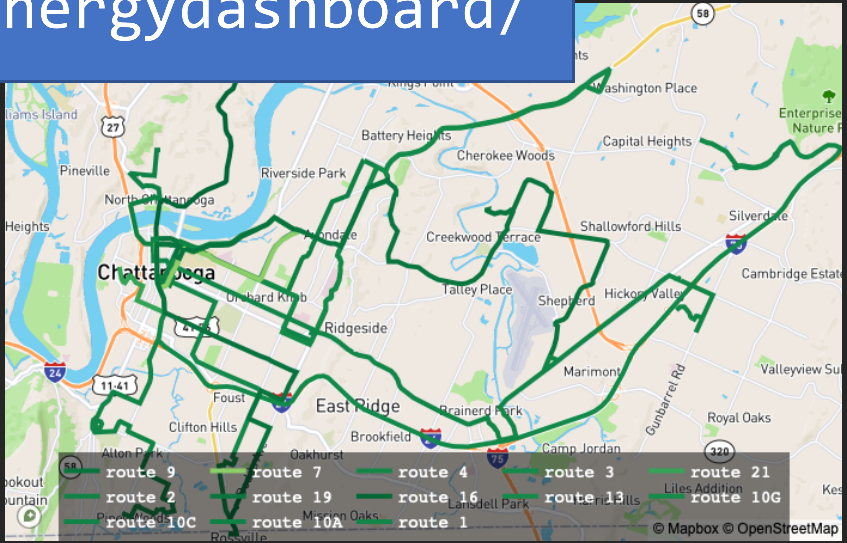


Online visualization dashboards:

https://smarttransit.ai/energydashboard/

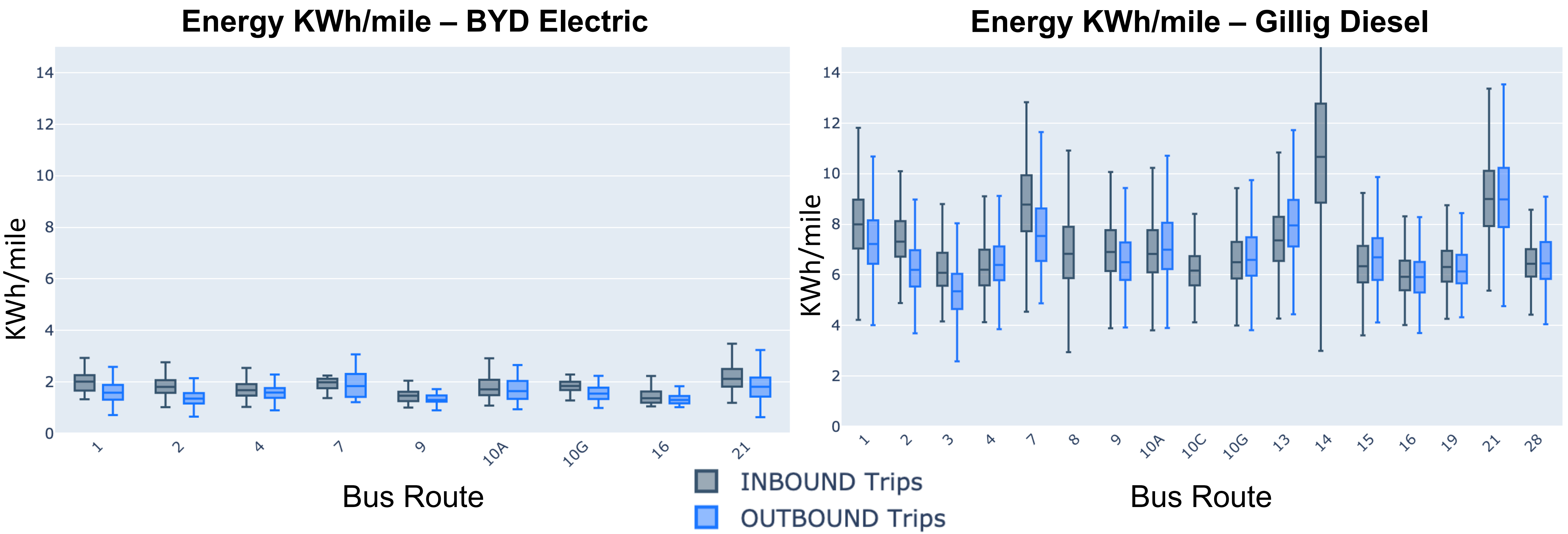


Energy Consumption Distribution by Time



Electrical Vehicle on Routes

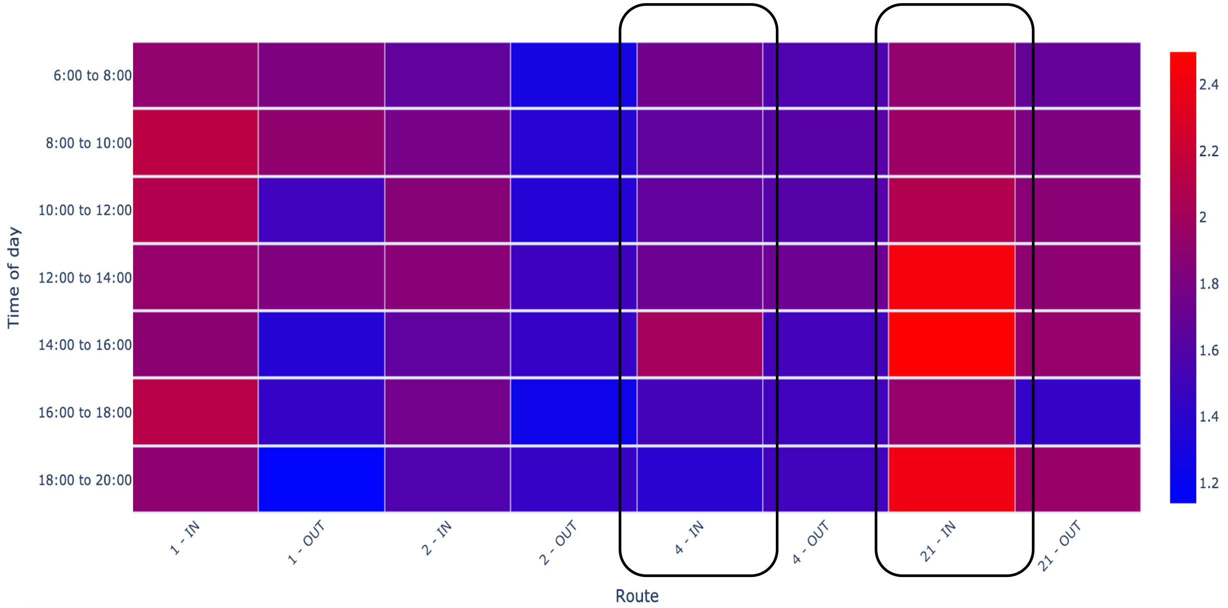
Analysis and Insights



- Boxplots show the KWh per mile for all trips on each route, data range from December 20, 2019 to April 15, 2020
- KWh per mile is higher for diesel vehicles compared to electric vehicles
- There is some variation between routes, which implies electric vehicles (agencies have limited numbers) can be deployed strategically to lower overall energy consumption
- Future work: we are analyzing the differences between vehicle models and years

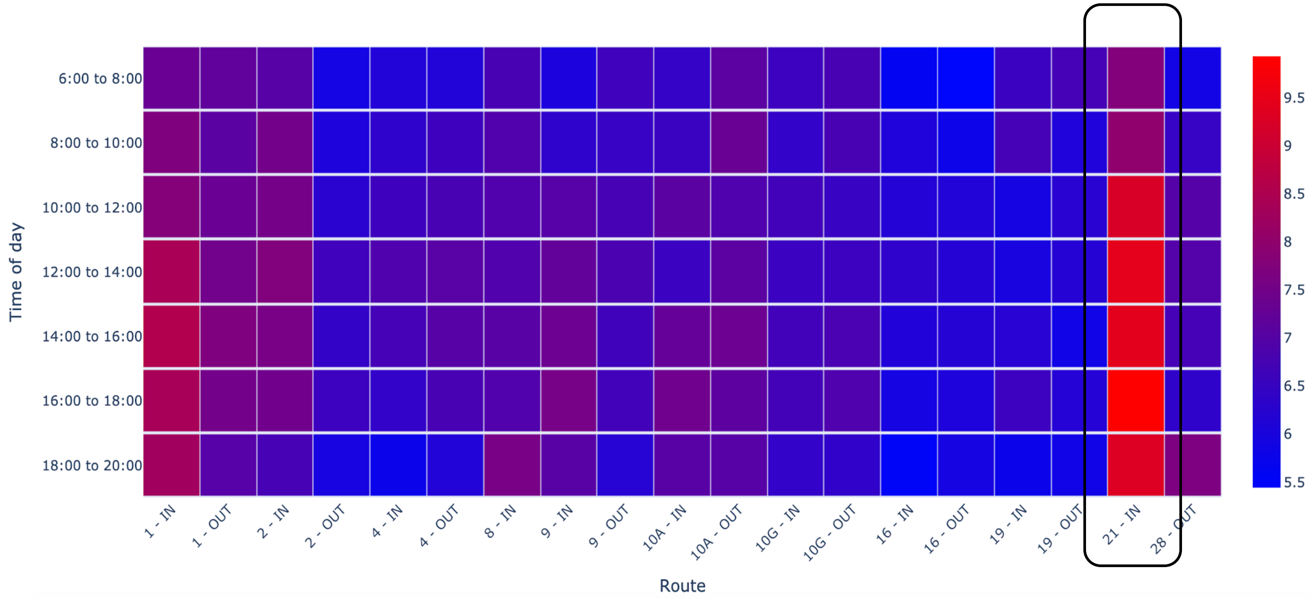
Analysis and Insights

Energy (kWh/mile) per route for BYD electric vehicles



Route 21 – has more stops and hilly terrain

Energy (kWh/mile) per route for Gillig diesel vehicles

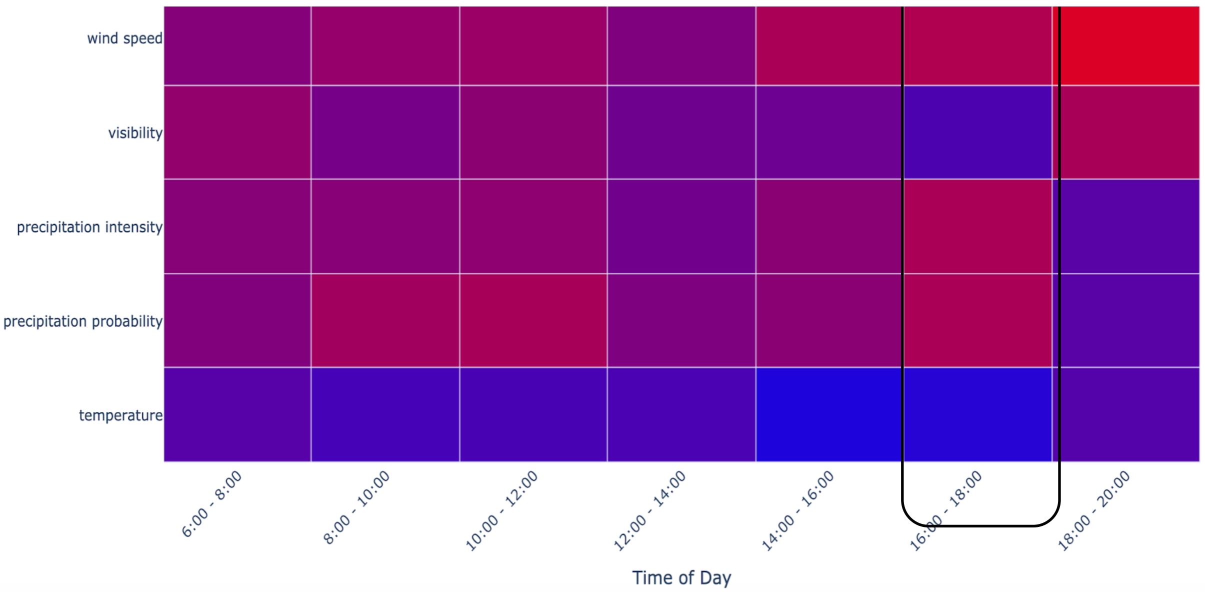


Route 21 – consumption is ~ 4 times more than electric

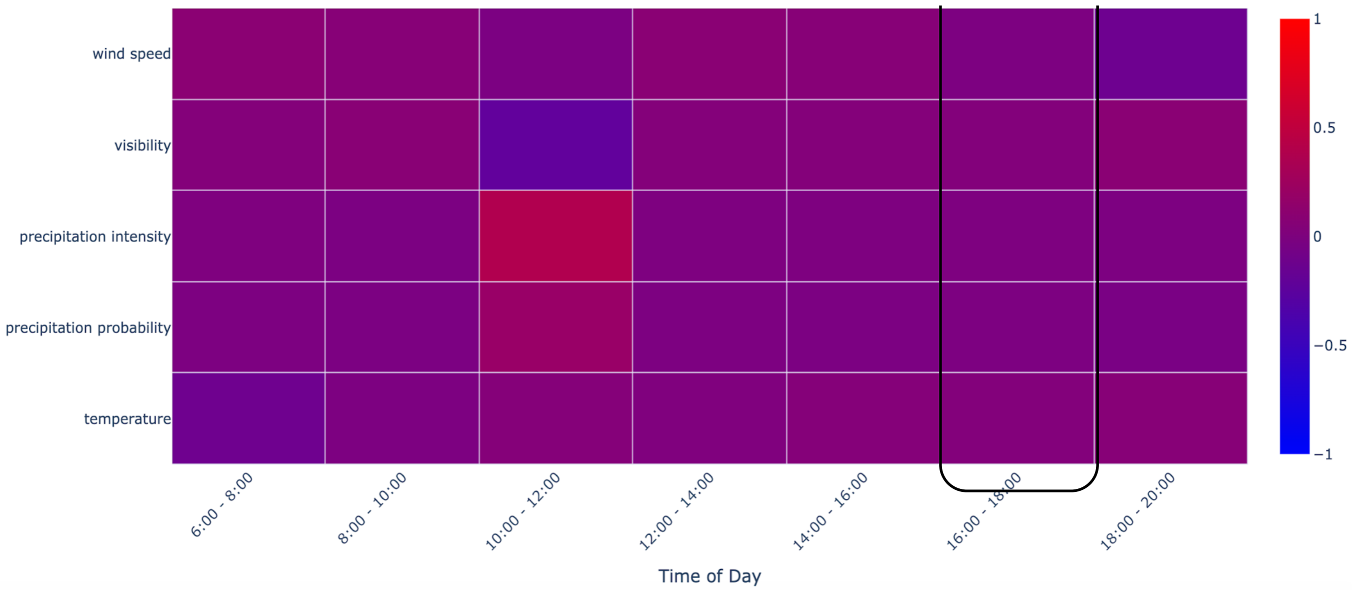
- Diesel vehicles are more affected by time of day than electric vehicles, which supports our hypothesis that electric vehicles perform better in dense traffic
- Scales of the heatmaps are different because of the difference in energy consumption magnitude between electric and diesel vehicles

Analysis and Insights

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



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



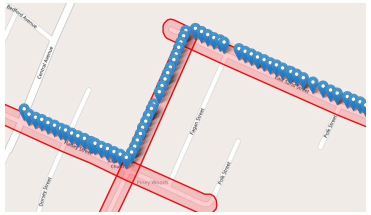
- Temperature has a negative correlation with energy cost for electric vehicles (as temperature goes up, energy cost goes down)
- Weather affects electric and diesel vehicles very differently and hence it is important identify correlation between features for each fleet separately
- Similarly, elevation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

2. Energy Usage Prediction

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

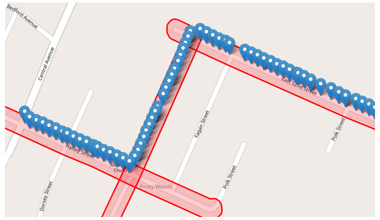
Predictor

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

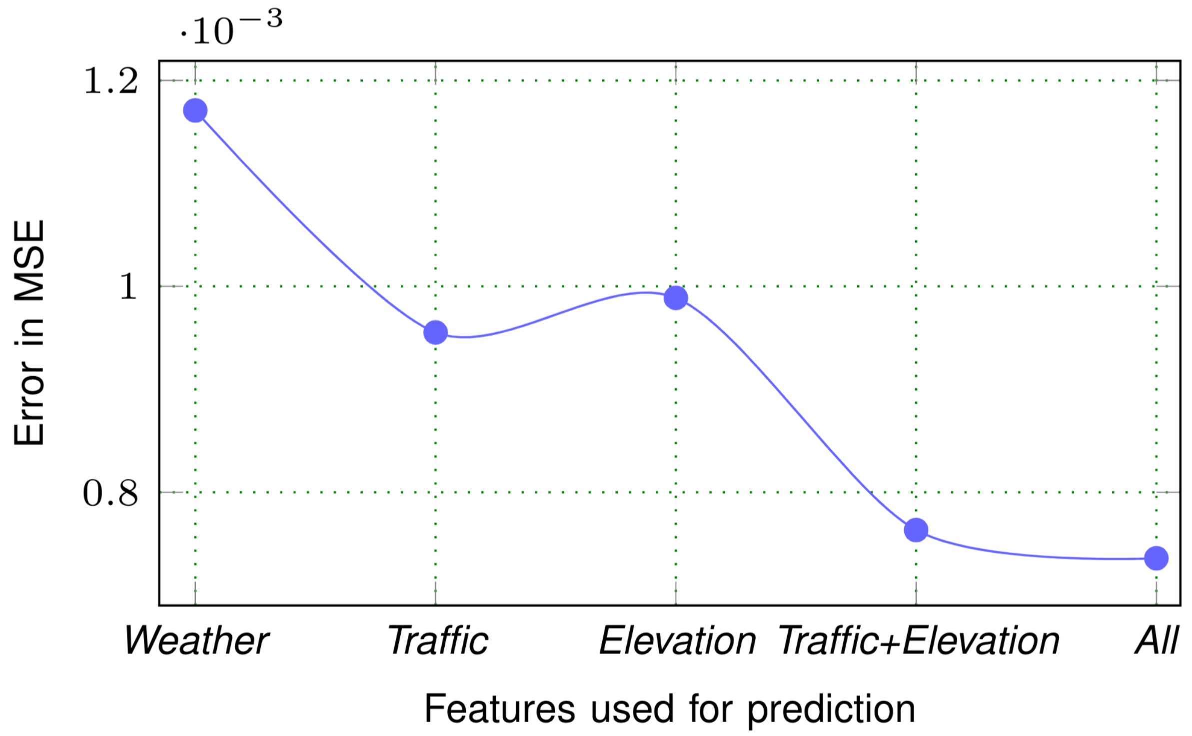
apply linear regression, decision tree, deep neural networks

Training, Evaluation, Prediction

Macroscopic Energy Prediction Results #1

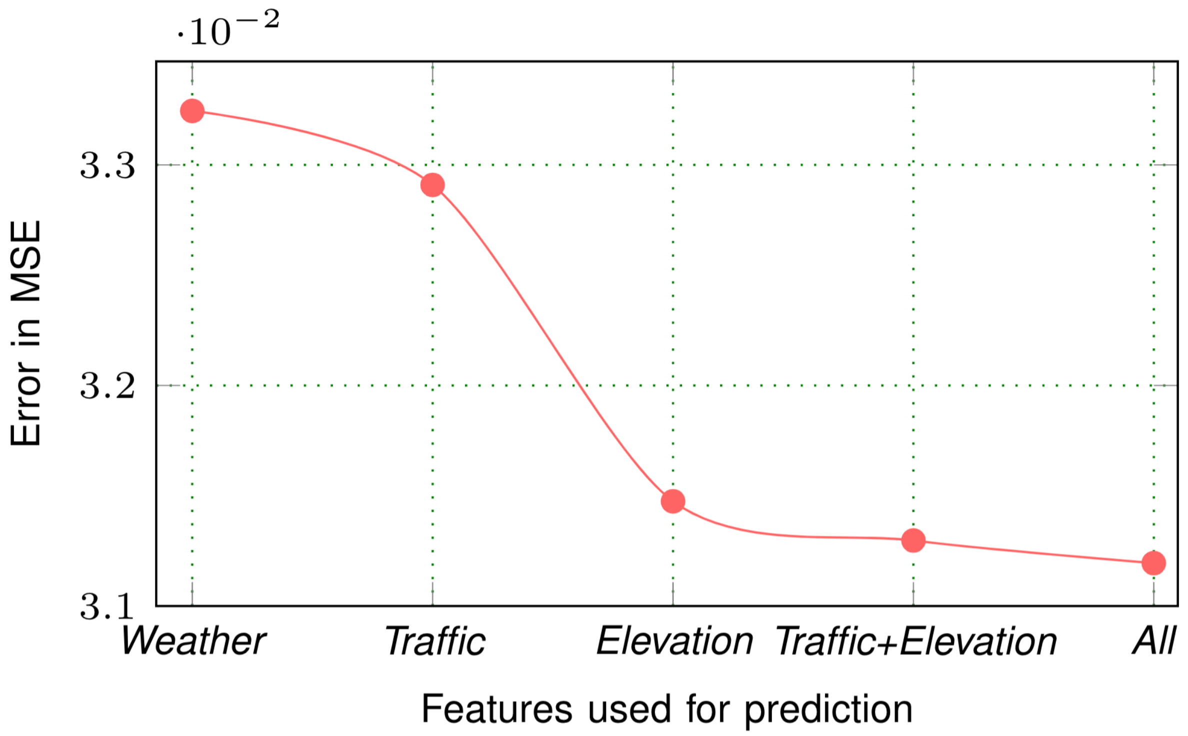
Which data features are the most useful for prediction?

Diesel (2014 Gillig Phantom)



Both elevation and traffic data are significant for diesel vehicles

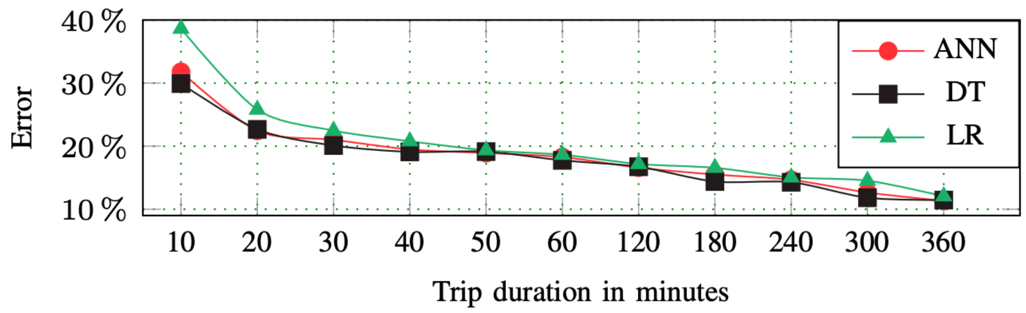
Electric (2016 BYD K9S)



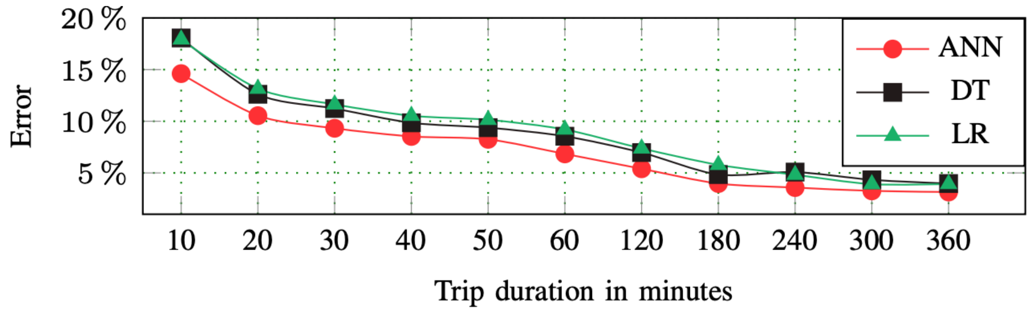
Elevation is by far the most significant feature for electric vehicles

Macroscopic Energy Prediction Results #2

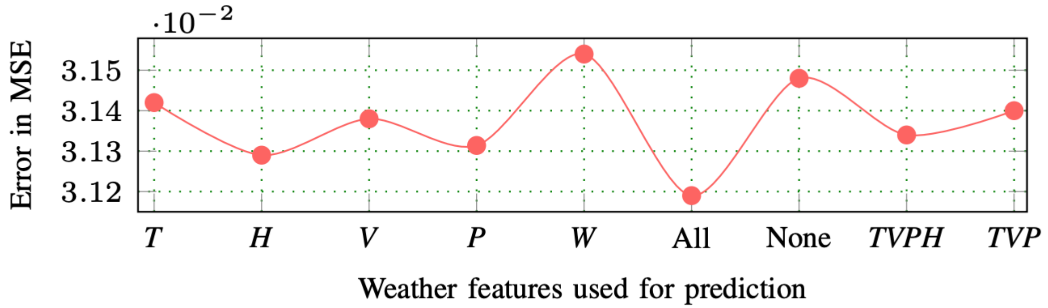
Electric

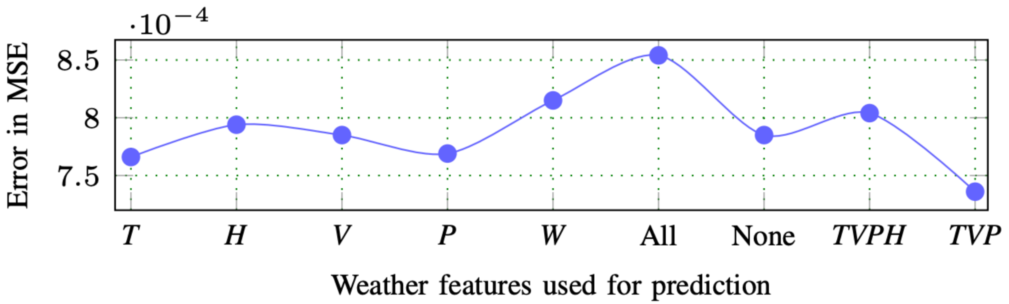


Diesel



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

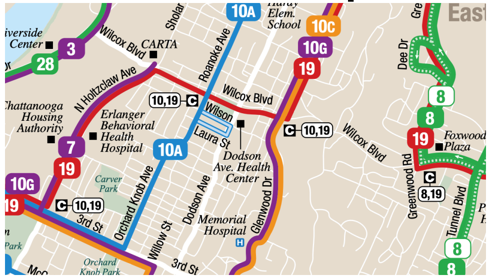
For diesel vehicles we attain lowest error using only three features: temperature, visibility and pressure (need further investigation)

3. Transit Optimization

Vehicle Assignment and Charging Optimization

- Motivation: **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)

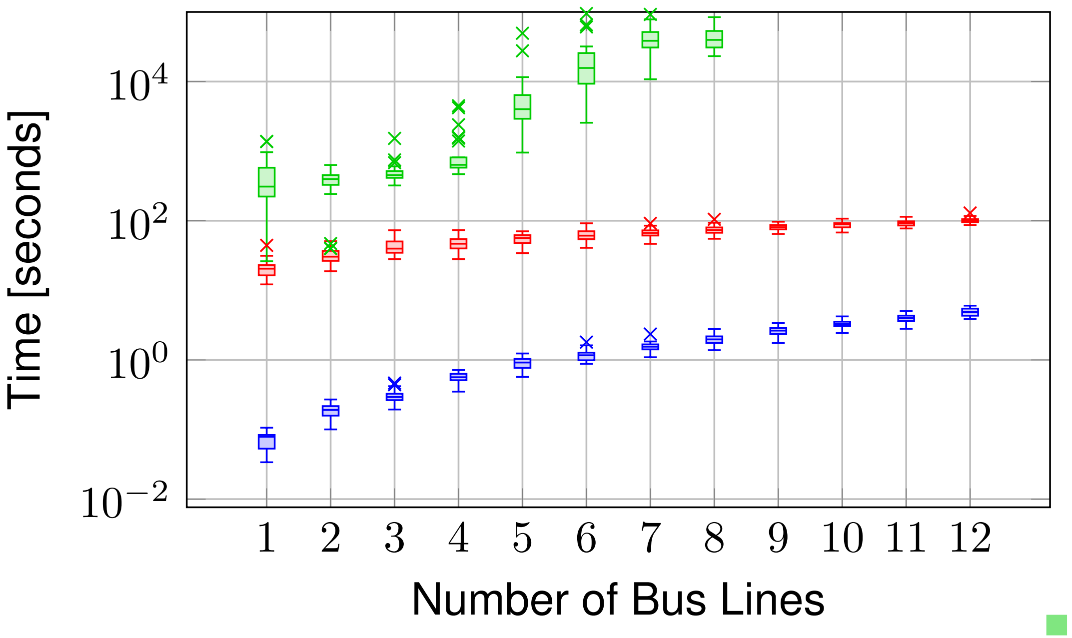
Charging

- Computational approaches (ongoing work)
  - **Integer program**: finds optimal solution, but does not scale well computationally
  - **Greedy algorithm**: very efficient computationally
  - **Simulated annealing**: computationally efficient, improves greedy algorithm with random search

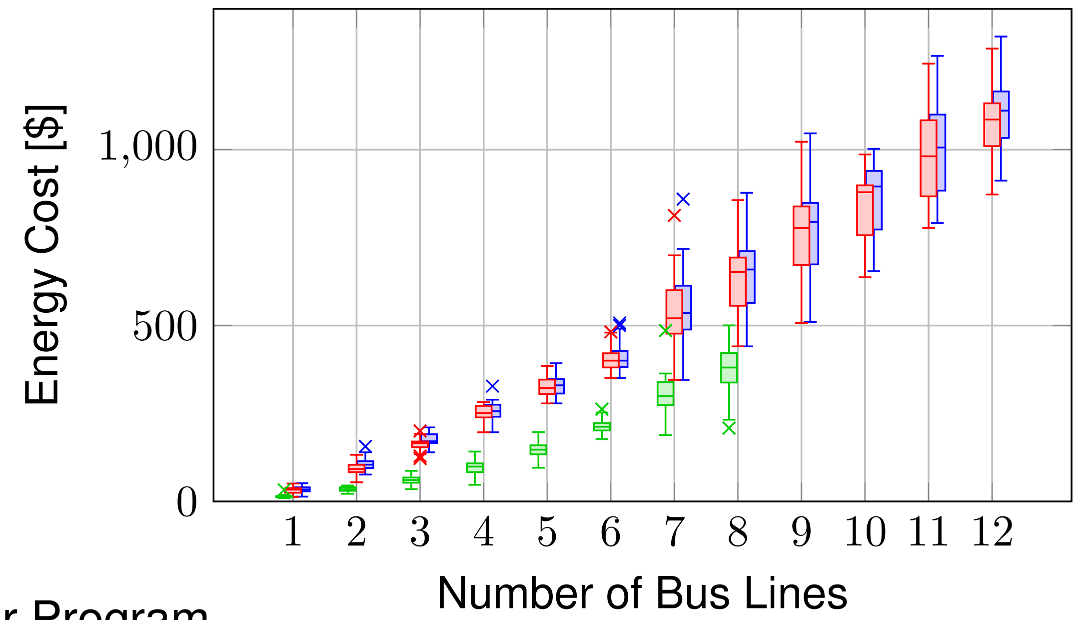
Optimization Results #1

How do the proposed algorithms perform?

Computational Complexity



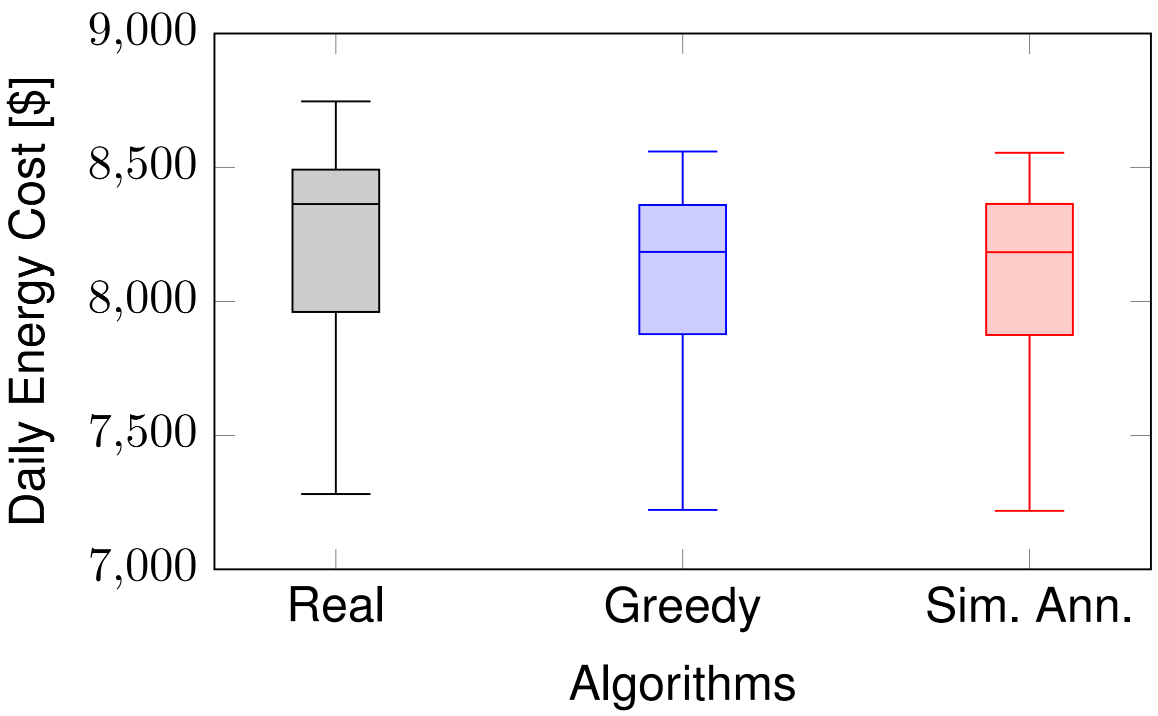
Energy Cost



Integer Program
Simulated Anneal.
Greedy Algorithm

Optimization Results #2

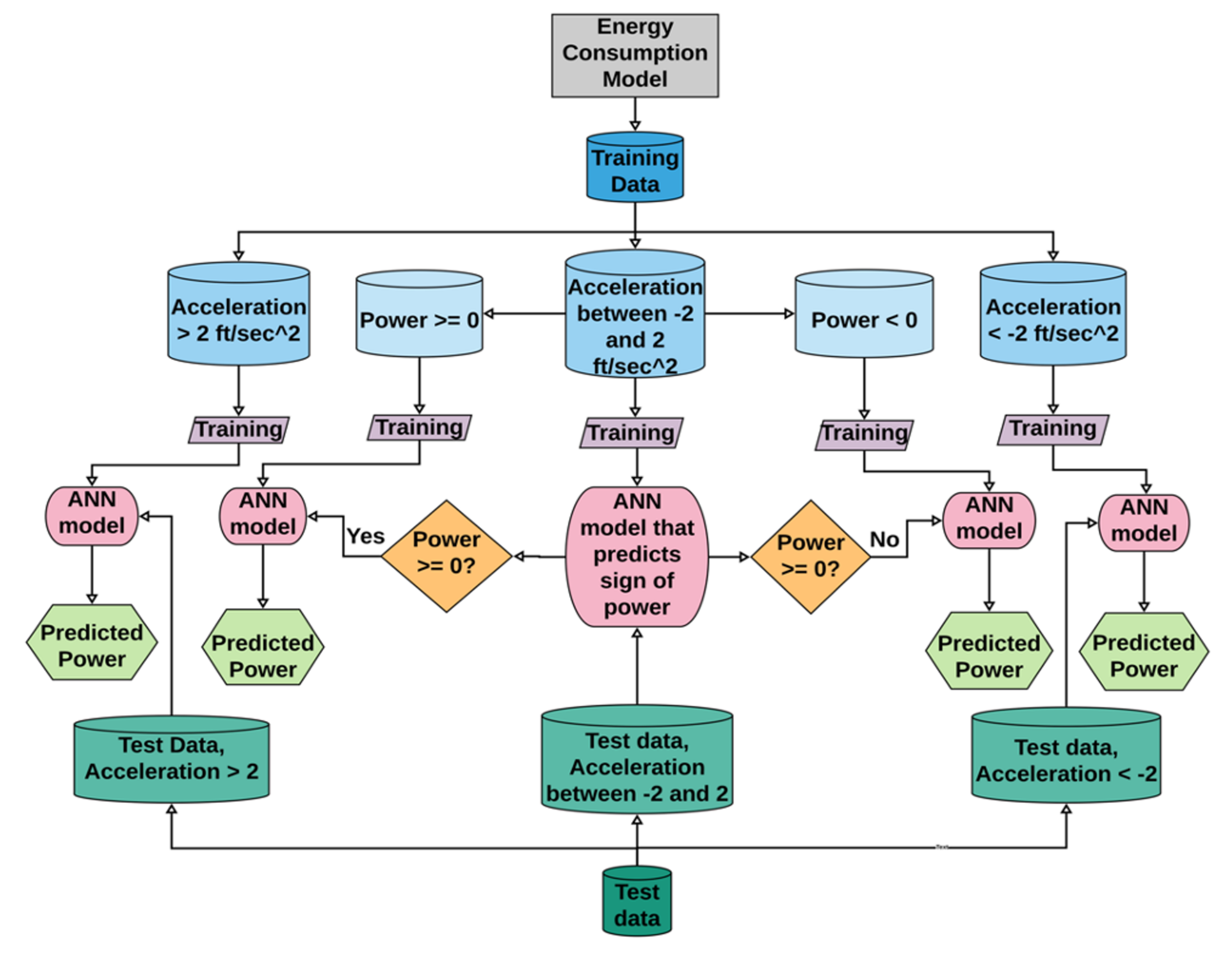
What are the potential savings in energy usage?



- We compute assignments for the daily schedule of CARTA with 3 electric and 50 diesel buses using greedy and simulated annealing algorithms
- Assignments found by simulated annealing lower daily costs by $134 and CO_2 emission by 0.48 metric tons
  → $48K and 175.2 tons of CO_2 saved annually

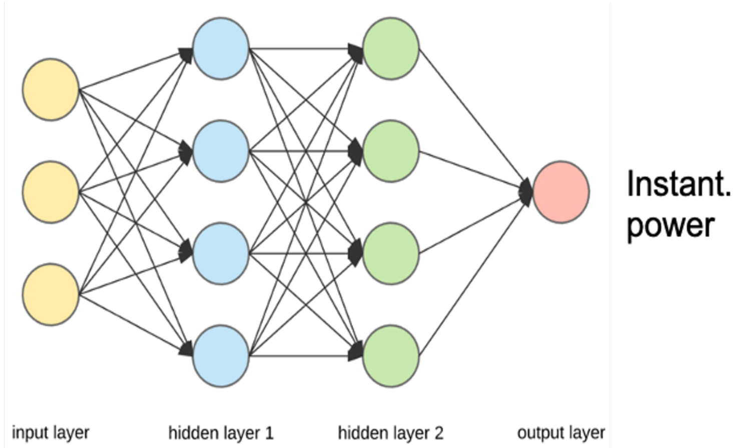
Microscopic Energy Prediction Model

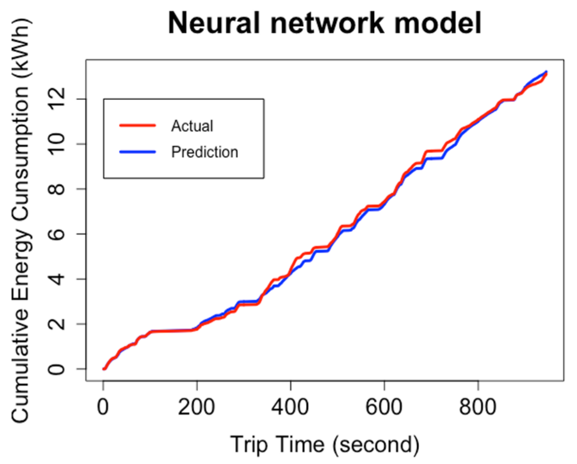
Classifying data based on driving features

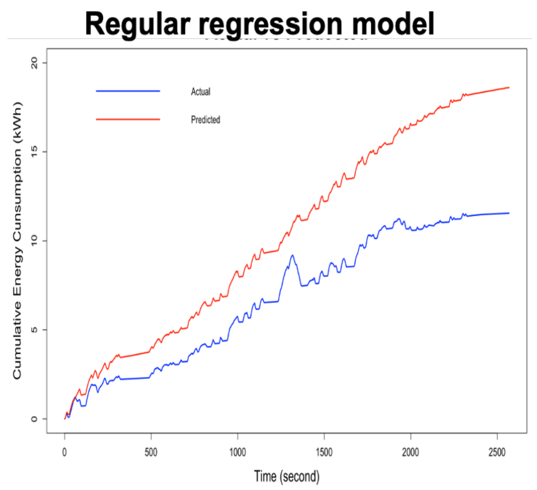


Variable and model selections for optimal prediction performance

Velocity
Acceleration
Road Grade
Weather/humidity
Weather/temperature





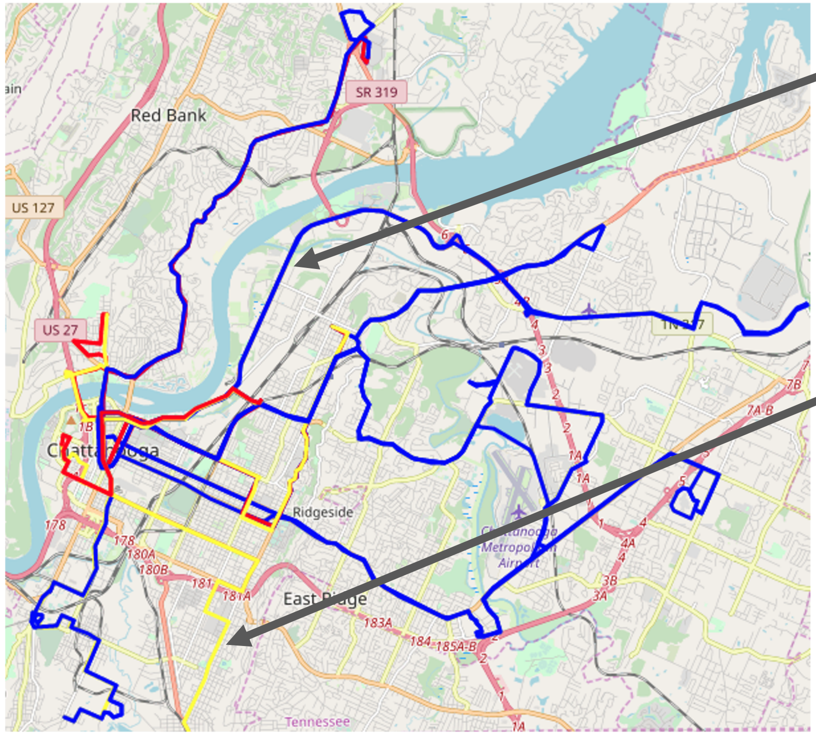


Visualization Framework for Operational Guidance

- 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

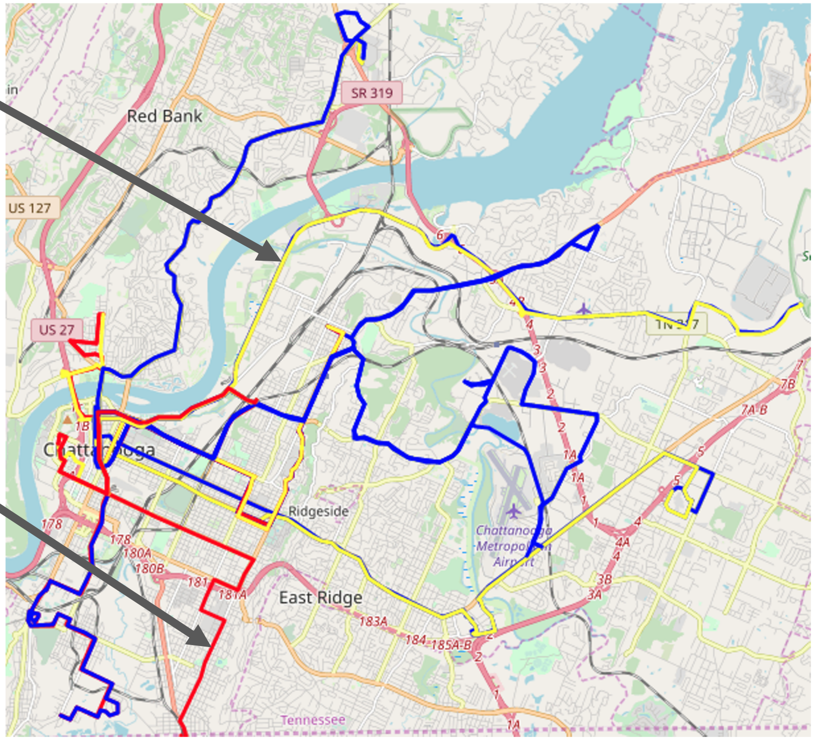
Energy consumption depends on route as well as time of day



6AM to 9AM

Legend: Energy Usage (Per Quantile)

Light (Q1 and Q2)	blue
Moderate-Heavy (Q3)	yellow
Heavy (Q4)	red



3PM to 6PM

Summary

Relevance

Reduce energy consumption of public transit fleet through vehicle optimization

Approach

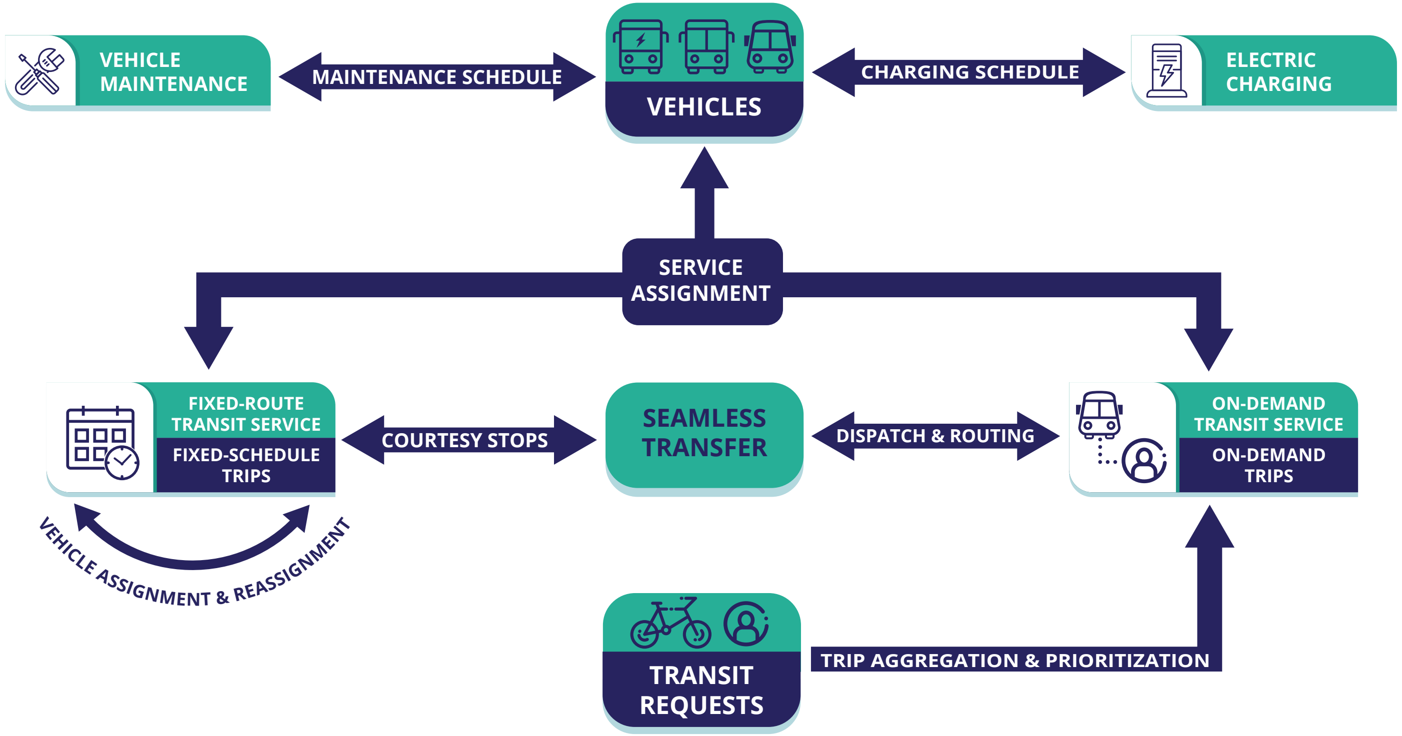
Collaborative partnership with transit agency operating mixed-vehicle fleet

Accomplishments

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

Related Transit Project by Our Team

- **AI-Engine for Optimizing Integrated Service in Mixed Fleet Transit Operations**
  - funded by the **Department of Energy**, **2021 – 2023**
  - idea: artificial intelligence for the integrated optimization of fixed-route and on-demand transit services



Related Transit Project by Our Team

- **AI-Engine for Optimizing Integrated Service in Mixed Fleet Transit Operations**
  - funded by the **Department of Energy**, **2021 – 2023**
  - idea: artificial intelligence for the integrated optimization of fixed-route and on-demand transit services to decrease energy usage
- **Mobility for all – Harnessing Emerging Transit Solutions for Underserved Communities**
  - funded by the **National Science Foundation**, **2021 – 2024**
  - idea: design a community-centric micro-transit services that augments fixed-line transit following a socio-relational approach to community engagement
- **Addressing Transit Accessibility Challenges due to COVID-19**
  - funded by the **National Science Foundation**, **2020 – 2021**

For more information, datasets, publications, etc., please visit

https://smarttransit.ai/

Thank You

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http://aronlaszka.com/