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

Chattanooga Area Regional Transportation Authority

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This presentation does not contain any proprietary, confidential, or otherwise restricted information.
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.
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

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

- 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 to identify correlation between features for each fleet separately.
- Similarly, elevation affects the vehicles differently.
- We utilize this sensitivity in planning the assignment problem.

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

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

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

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

Calculate Energy Consumption
- consumption time series from using battery current and voltage or fuel levels

Train, Evaluation, Prediction

Machine Learning Models
- apply linear regression, decision tree, deep neural networks

Generate 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

Accomplishments & Progress
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*
Accomplishments & Progress

Macroscopic Energy Prediction Results #2

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

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

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

  - Transit trips
  - Vehicles (ICEV and EV)
  - 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**

- Time [seconds]
- Number of Bus Lines
- Heuristic L, LP, IP

**Energy Cost**

- Energy Cost [$]
- Number of Bus Lines
- Heuristic L, Heuristic B, GA, IP, LP
Microscopic Energy Prediction Model

Classifying data based on driving features

Variable and model selections for optimal prediction performance

Accomplishments & Progress

- Velocity
- Acceleration
- Road Grade
- Weather/humidity
- Weather/temperature

![Diagram of Energy Consumption Model]

- Training Data
- Acceleration > 2 ft/sec^2
- Power >= 0
- Acceleration between -2 and 2 ft/sec^2
- Power < 0
- Acceleration < -2 ft/sec^2

- ANN model
- Predicted Power
- Test Data, Acceleration > 2
- Test Data, Acceleration between -2 and 2
- Test Data, Acceleration < -2

- Instant power

- Input layer
- Hidden layer 1
- Hidden layer 2
- Output layer

Neural network model

- Actual
- Prediction

Regular regression model

Cumulative Energy Consumption (kWh)

Trip Time (second)
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
Energy consumption depends on route as well as time of day.

Visualization: Historical Trends

6AM to 9AM

3PM to 6PM
Collaboration and Coordination

**Core Team**
- CARTA – Prime
  - Vehicle data telemetry
- Vanderbilt University
  - Data store architecture
- University of Houston
  - Macro prediction models
- University of South Carolina
  - Micro predictions models

**Community Coordination**
- City of Chattanooga Department of Transportation and Smart Cities office
- The Enterprise Center
- East Tennessee Clean Fuels Coalition
  - Weekly video conference call
  - Shared data access
  - Conference collaboration
Market Impact & Sustainability

❖ Outcomes Achieved
  ✓ Data Collection and Training Framework
  ✓ Data-Driven Predictors for Contextual Energy Consumption
  ✓ Model-Driven Predictors for Ensuring Transference for Application to Other Cities
  ✓ Publication of project code repository and collaborative notebooks for system replication

❖ Pending accomplishments in 2020
  ➢ Pilot testing of Operational Guidance System
  ➢ Completion of vehicle telematics integration
  ➢ Establishment of locally managed database and server at CARTA
  ➢ Final telemetry installations delayed due to COVID-19 restrictions

Any proposed future work is subject to change based on funding levels.
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.
Technical Back-up Slides
Macro Energy Prediction

• Artificial neural network (ANN) outperforms other models for both electric and diesel vehicles.

• We found that different network structures work best for diesel and electric vehicles.

• Electric Vehicles
  • The best model has one input, two hidden, and one output layer.
  • The input layer has one neuron for each predictor variable.
  • The two hidden layers have 100 neurons and 80 neurons, respectively.

• Diesel Vehicles
  • The model needs one input, five hidden layers, and one output layer.
  • The five hidden layers have 400, 200, 100, 50, and 25 neurons, respectively.

• Higher complexity points to the differences in underlying dynamics.
Optimal Vehicle Assignment Problem

• We consider a mixed transit fleet.
• We assume that electric vehicles have a limited capacity and needs charging.
• We assume that charging is only available at specific locations and there is a limit to how many vehicles can charge at the same time.
• We assume that the cost of charging is different at different times of the day.
• We use the predictive models we have constructed to determine the energy cost of operating a vehicle of specific type on a route at a given time when the weather is known.
• Our problem formulation determines optimal assignment of vehicles to trip such that overall energy consumption is lowest.
• The constraint is primarily the availability of electric vehicles and time it takes to charge them.
The Data Store Challenge and Approach

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

Zookeeper
- 5 Nodes
  - 1 VPU
  - 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
Reviewer Only Slides
• Poster at 2019 Tennessee Sustainable Transportation Forum & Expo
• Energy, electrification and evaluation: Data driven public transit. Presentation invited at 17th Transportation Research Board Tools of the Trade conference.