Minimizing Energy Use of Mixed-Fleet Public Transit for Fixed-Route Service

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MOTIVATION

- More than **28%** of the energy usage in the U.S. is from transportation [1]
- Public transit is responsible for **21.1** million metric tons of CO_2 emission in the U.S. [2]
- Adopting electric vehicles can reduce the environmental impact

But electric vehicles have

- High upfront costs
- Need for Charging infrastructure
- Limited battery capacity
- Longer charging duration

MOST TRANSIT AGENCIES CAN AFFORD ONLY MIXED FLEETS OF VEHICLES!

Energy usage of EVs and ICEVs can vary by **the nature of the route and time of the day**

THUS, PLANNING IS CRUCIAL FOR TRANSIT AGENCIES OPERATING MIXED FLEETS OF VEHICLES

- Which vehicle to be assigned to which route at a specific time of the day ?
- Which charging station to assign to which electric vehicle ?

GOAL: Minimize the energy usages of trip assignments and charging schedule given a mixed fleet of vehicles and fixed-route transit schedule

PREREQUISITE: Energy estimates for EVs and ICEVs for a given route at a given time of the day

We partnered with the Chattanooga Area Regional Transportation Authority (CARTA) to obtain energy estimates from real world data

MODEL AND PROBLEM FORMULATION

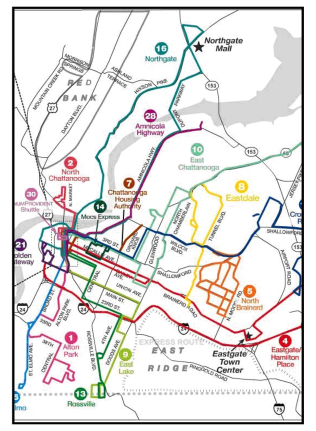
Vehicles:

Electric vehicles
- Limited battery capacity
- Needs to charge within the day

Internal-combustion engine (ICE) vehicles
- Can serve throughout the day without refueling

Transit Trips:

Each trip in schedule has a fixed
- Route
- Origin
- Destination
- Start time
- End time
- Stops



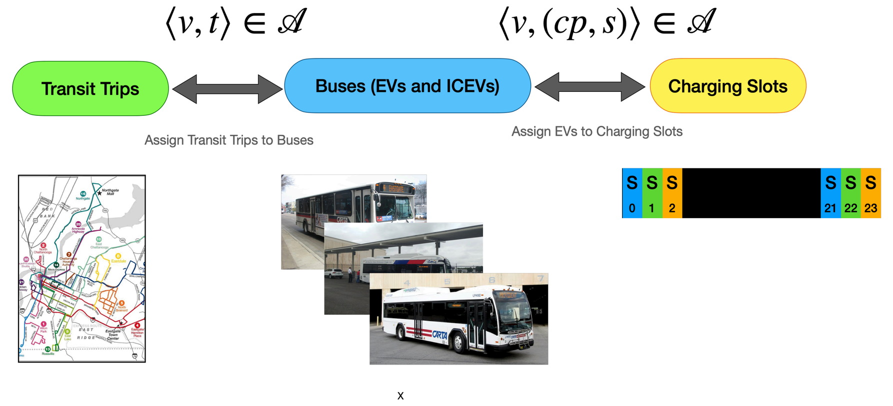
Charging Slots:

- Day is divided into disjoint set of slots
- Each slot has a fixed duration (e.g., 15 minutes, 30 minutes, 1 hour)
- Combination of a charging pole and a slot is collectively known as a charging slot

Constraints:

- Each trip in the schedule needs to be assigned to one bus
- There must be enough time between two consecutive assignments to get from the destination of the preceding to the origin of the following
- Only one EV can be charged at a charging slot
- EVs requires enough energy to serve the trip

Solution Representation:



Objective:

Minimizing energy costs for **transit trips** and **non-service trips**

$$\min_{\mathcal{A}} \sum_{v \in \mathcal{V}: M_v \in \mathcal{M}^{gas}} K^{gas} \cdot e(\mathcal{A}, v, s_\infty) + \sum_{v \in \mathcal{V}: M_v \in \mathcal{M}^{elec}} K^{elec} \cdot e(\mathcal{A}, v, s_\infty)$$

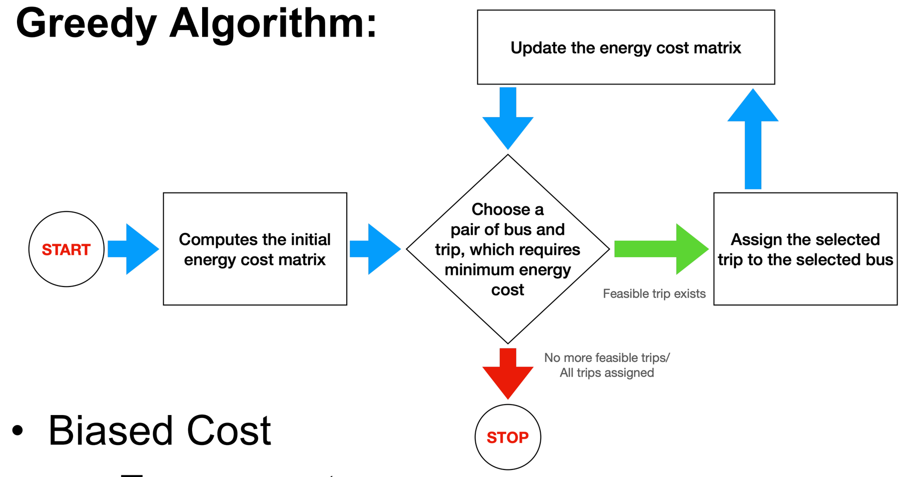
ALGORITHMS

The optimization problem is NP-hard!

- We formulated a mathematical model to optimize the energy usage in transit agencies operating mixed-fleet vehicles with a given transit schedule
- We present an **Integer Programming** (IP) that provides the optimal assignment and scheduling

Since IP is computationally infeasible for large transit networks, we have implemented polynomial time heuristic and meta-heuristic algorithms to solve larger transit networks.

Greedy Algorithm:



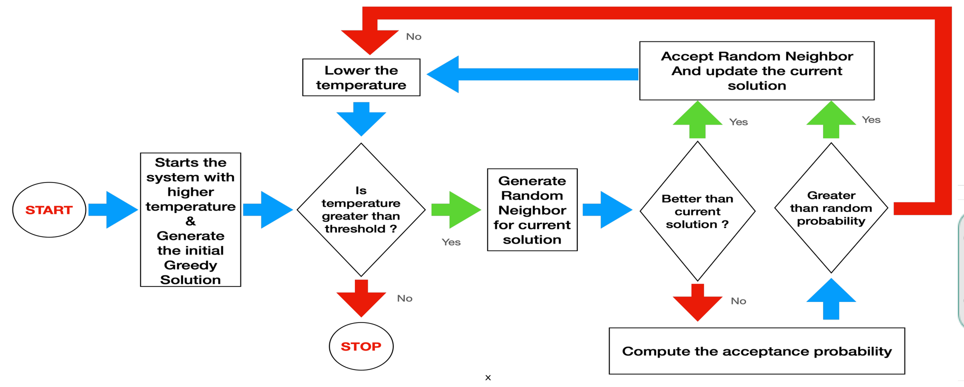
- Biased Cost
  - Energy costs for serving transit trip
  - Energy costs associated with non-service trip
  - Wait-time between consecutive trips

Motivation for factoring in wait-time

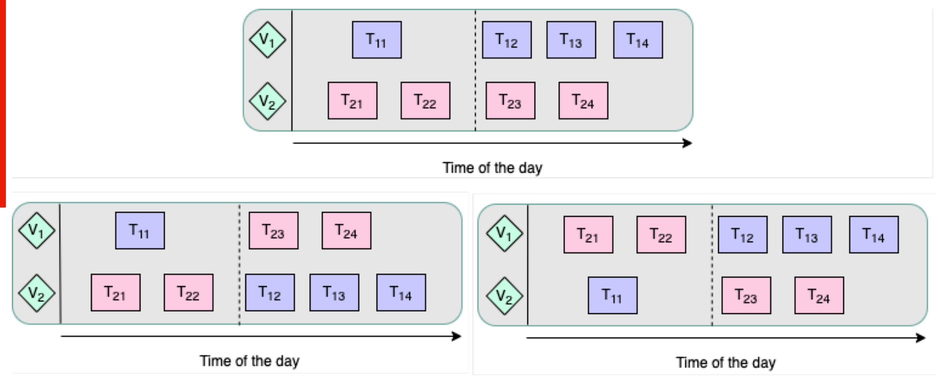
- Increases bus utilization
- Decreases longer waiting period

We enhance the solution quality of our greedy solution using simulated annealing

Simulated Annealing:



Random Neighbor:



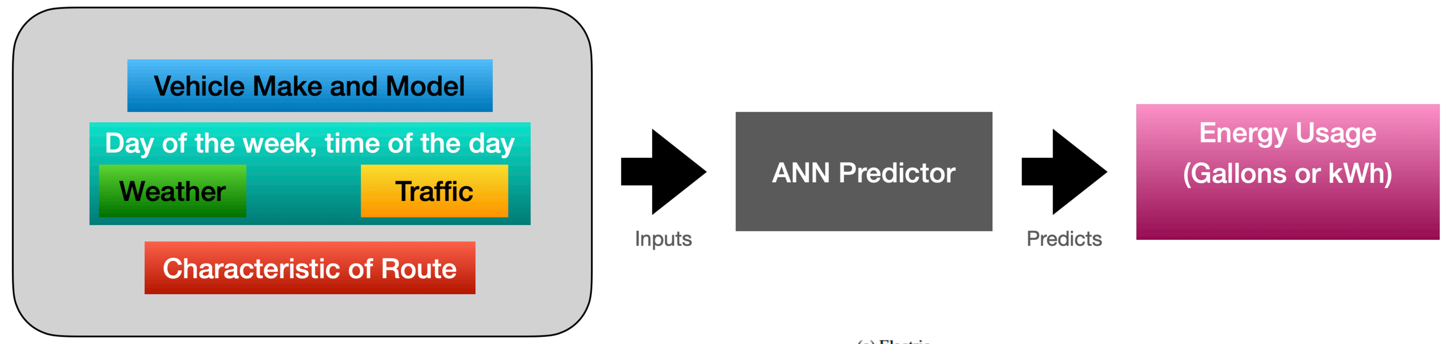
NUMERICAL RESULTS

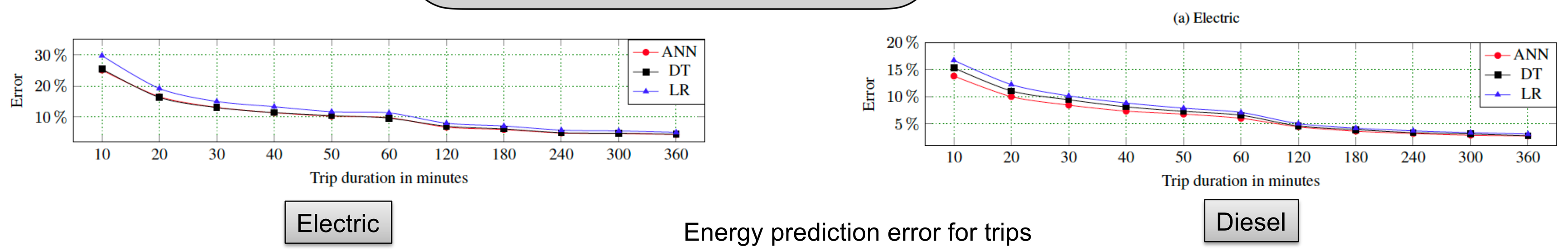
Data Collection:

- From ViriCiti on-board devices, we obtain vehicle locations and past energy consumption
- From DarkSky API, we obtain weather data
- From HERE Maps, we obtain traffic data

Data	Source	Frequency	Scope	Features
Diesel Vehicles (2014 Gillig Phantom)	ViriCiti & CARTA	1 Hz	3 vehicles for 7 months (veh. IDs: 148, 149, 150; 2019-8-22 to 2020-03-31)	GPS location, fuel-level, fuel rate, odometer
Electric Vehicles (2016 BYD K9S 35-foot battery-electric buses)	ViriCiti & CARTA	1 Hz	3 vehicles for 7 months (veh. IDs: 751, 752, 753; 2019-8-22 to 2020-03-31)	GPS location, charging status, battery current, battery voltage, battery state of charge, odometer
Traffic	HERE	1 Hz	TMC Segments for major roads Chattanooga Region	TMC ID, unconstrained speed, free-flow speed, jam factor
Weather	DarkSky	0.1 Hz	Chattanooga Region	Location, temperature, visibility, humidity, precipitation, wind speed
Elevation	TN GIC	Static	Chattanooga Region	Location, elevation

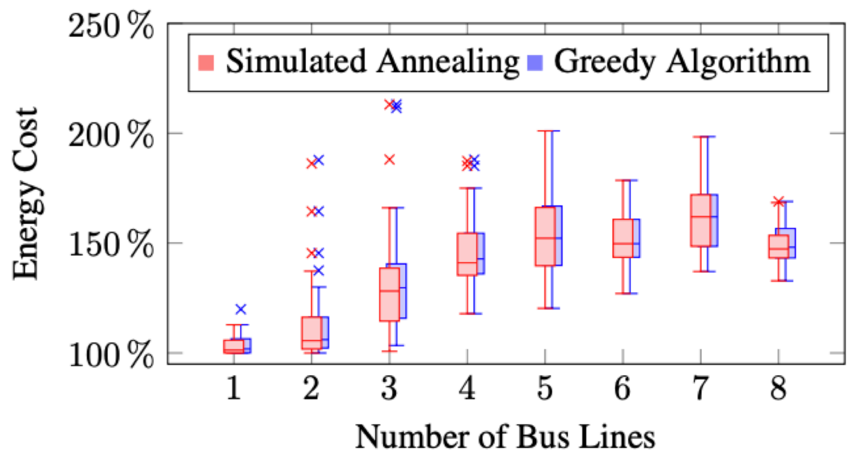
We use **Artificial Neural Network (ANN)** to predict energy usage from collected data



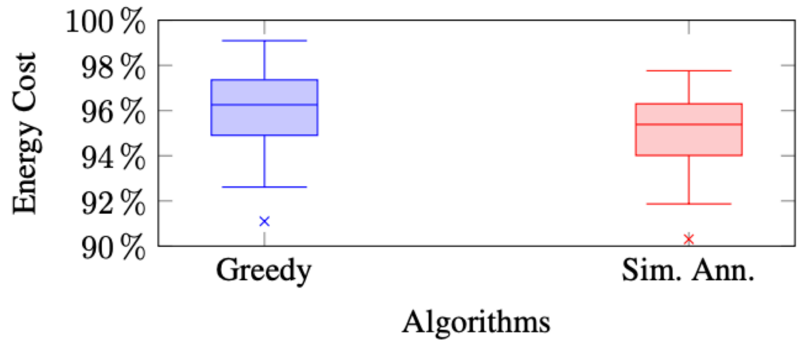


A. Ayman, A. Sivagnanam, M. Wilbur, P. Pugliese, A. Dubey, and A. Laszka, **Data-Driven Prediction and Optimization of Energy Use for Transit Fleets of Electric and ICE Vehicles**, *ACM Transactions of Internet Technology*, in press.

- We evaluated the computational time and solution quality of our heuristics and meta heuristics compared with integer programming
- As the number of bus lines increases, integer programs become infeasible to solve



- The ratio between the energy costs of our heuristic algorithms and the optimal solutions remain within the range of 1.5 – 1.6 for 5 to 8 bus lines
- We compared the performance of our algorithms for complete daily schedules with current real-world assignments of the **Chattanooga Area Regional Transportation Authority**



Annually, we can save $145k in energy cost and reduce CO_2 emission by 576.7 metric tons

CONCLUSIONS

- We introduced a novel problem formulation of minimizing the energy usage of a public transit agency operating a mixed fleet of vehicles, without changing the fixed transit schedule
- We proposed heuristic and meta-heuristic algorithms to solve the problem for larger networks
- Based on real-world data, our algorithms scale well and reduce energy usage
- As a future work, we focus on improving the gap between our algorithms and the optimum

REFERENCES

[1] EIA. 2019. U.S. Energy Information Administration: Use of energy explained – Energy use for transportation (2019). https://www.eia.gov/energyexplained/use-of-energy/transportation.php

[2] EPA. 2020b. U.S. Transportation Sector Greenhouse Gas Emissions. https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey = P100ZK4P.pdf

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