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

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Introduction

- **28%** energy usage in U.S. [1] is from transportation

- In U.S., public transportation is responsible for **21.1 million metric tons of CO₂ emission** [2]

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[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
Introduction

• Adopting electric vehicles
  • Reduces greenhouse gas emissions and operational costs

• Challenges
  • EVs cost around $1M (including charging infrastructure)
    • TWICE as much as ICEVs
  • Limited battery capacity and driving range.
  • Longer charging duration.

MOST TRANSIT AGENCIES CAN AFFORD ONLY MIXED FLEETS OF VEHICLES!
Introduction

• Energy usage of EVs and ICEVs can vary based on
  • The nature of the route
  • The time of the day

• **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 **Chattanooga Area Regional Transportation Authority (CARTA)**, and obtain the energy estimates using real world data.

**THUS PLANNING IN TRANSIT AGENCIES WITH MIXED FLEETS IS CRUCIAL**

• Which vehicle to be assigned to which route at a specific time of the day?

• Which charging station to assign to which electric vehicle?
**Model**

**Vehicles - (\(\mathcal{V}\))**

- Electric Vehicles (\(v \in \mathcal{V} \land M_v \in M_{\text{elec}}\))
  - Limited Battery Capacity (\(C_m\))
  - Needs to charge within the day
- ICE Vehicles (\(v \in \mathcal{V} \land M_v \in M_{\text{gas}}\))
  - Can serve throughout the day without refueling

**Transit Trips - (\(\mathcal{T}\))**

- Each trip \(t\) (\(t \in \mathcal{T}\)) in schedule has a fixed
  - Route
    - Origin (\(t_{\text{origin}}\))
    - Destination (\(t_{\text{destination}}\))
  - Start time (\(t_{\text{start}}\))
  - End time (\(t_{\text{end}}\))
  - Stops

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Transit map image
Model
Charging Slots ($\mathcal{C}$)

- Day is divided into disjoint set of slots ($\mathcal{S}$).
- Each slot has a fixed duration (e.g. 15 minutes, 30 minutes, 1 hour).

- Combination of a charging pole $cp$ ($cp \in \mathcal{CP}$) and a slot $s$ ($s \in \mathcal{S}$) is collectively known as a charging slot $c$ ($c \in \mathcal{C}$).
Model

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

∀t₁, t₂ ∈ ℰ; t_{start₁} ≤ t_{start₂}, ⟨v, t₁⟩ ∈ ℬ; ⟨v, t₂⟩ ∈ ℬ : t_{end₁} + D(t_{destination₁}, t_{origin₂}) ≤ t_{start₂}

• Only one EV can be charged at a charging slot

• EVs requires enough energy to serve the trip

∀v ∈ ℱ, ∀s ∈ ℳ : 0 < r(ℬ, v, s) − e(ℬ, v, s) ≤ C_{M_v}
Model
Solution Representation

\[ \langle v, t \rangle \in \mathcal{A} \]

Transit Trips  \rightarrow  Buses (EVs and ICEVs)  \rightarrow  Charging Slots

Assign Transit Trips to Buses  \hspace{1cm} Assign EVs to Charging Slots

\[ \langle v, (cp, s) \rangle \in \mathcal{A} \]
Minimizing energy costs for transit trips and non-service trips.

\[
\min \sum_{\mathcal{A}, v \in \mathcal{V} : M_v \in \mathcal{M}} K_{\text{gas}} \cdot e(\mathcal{A}, v, s_\infty) + \sum_{\mathcal{A}, v \in \mathcal{V} : M_v \in \mathcal{M}} K_{\text{elec}} \cdot e(\mathcal{A}, v, s_\infty)
\]
Algorithms

The optimization problem is **NP-Hard**!

- Integer Program
  - provides optimal solution, infeasible for larger problem instances.
- Greedy Approach
  - computes the solution quickly.
- Simulated Annealing
  - enhance the solution obtained from greedy.
Greedy Algorithm

START

Computes the initial energy cost matrix

Choose a pair of bus and trip, which requires minimum energy cost

Assign the selected trip to the selected bus

Update the energy cost matrix

STOP

Feasible trip exists

No more feasible trips/ All trips assigned
Greedy Algorithm

Biased Cost

• Energy costs for serving transit trip: $E(v, x)$

• Energy costs associated with non-service trip: $(E(v, m_{prev}), E(v, m_{next}))$

• Wait-time between consecutive trips: $(\alpha \cdot (x_{start} - x_{prev}), \alpha \cdot (x_{end} - x_{next}))$

• Motivation for factoring in wait-time
  • Increases bus utilization.
  • Decreases longer waiting period.
Simulated Annealing

START

Starts the system with higher temperature & Generate the initial Greedy Solution

Lower the temperature

Is temperature greater than threshold?

Yes

Generate Random Neighbor for current solution

Better than current solution?

Yes

Accept Random Neighbor And update the current solution

No

Greater than random probability

Yes

Compute the acceptance probability

No

STOP
Simulated Annealing
Random Neighbor Algorithm
Results
Experimental Setup

• Transit schedule from the GTFS dataset of our partner agency, CARTA
  • **17** Routes, **850+** Daily Trips
  • **3** EVs and **50** ICEVs

• Non-service trips between CARTA locations from Google Directions API

• Energy estimates from our energy predictors

The data and code are available at [https://smarttransit.ai/](https://smarttransit.ai/)
Results

Data Collection for Energy Prediction

- Obtain real data from sensors
  - Vehicle location
  - Energy usages
- Obtain weather data from DarkSky
- Obtain traffic data from HERE maps

The data and code are available at [https://smarttransit.ai/](https://smarttransit.ai/)
Results
Energy Prediction

• We use Artificial Neural Network (ANN) to predict energy estimates from collected data
Results
Smaller Problem Instances
Results

Complete Daily Schedule

- We compare the performance of our greedy and simulated annealing algorithm for complete daily schedules for different sample days, with the full fleet of CARTA.

- Daily
  - saves $399 of Energy Cost
  - reduces 1.58 metric tonnes of CO$_2$

- Annually
  - saves $145k of Energy Cost
  - reduces 576.7 metric tonnes of CO$_2$
Conclusion

• We formulated novel problem formulation of minimizing operating costs and environment impact through assigning trips to vehicles and assigning EVs to charging.

• We provide efficient greedy and simulated annealing algorithms.

• For complete daily schedule simulated annealing takes around 8 hours (50000 iterations).

• Our algorithms reduce energy costs and CO₂ emissions for complete daily schedule compared to real world assignments.

• Performance of our heuristics and meta heuristics with respect to IP can be improved further.

• In future work, we will focus on reducing the gap between optimal solution and our heuristics.
Thank You For The Attention!

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Q & A

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