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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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.
Model

Vehicles - ($\mathcal{V}$)

- Electric Vehicles ($v \in \mathcal{V} \land M_v \in \mathcal{M}^{\text{elec}}$)
  - Limited Battery Capacity ($C_m$)
  - Needs to charge within the day
- ICE Vehicles ($v \in \mathcal{V} \land M_v \in \mathcal{M}^{\text{gas}}$)
  - 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
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 $cp$ ($cp \in \mathcal{C} \mathcal{P}$) 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

\[ \forall t_1, t_2 \in \mathcal{T}; \quad t_1^{\text{end}} + D(t_1^{\text{destination}}, t_2^{\text{origin}}) \leq t_2^{\text{start}} \]

- Only one EV can be charged at a charging slot
- EVs requires enough energy to serve the trip

\[ \forall v \in \mathcal{V}, \forall s \in \mathcal{S} : \quad 0 < r(\mathcal{A}, v, s) - e(\mathcal{A}, v, s) \leq C_{Mv} \]
Model
Solution Representation

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

Transit Trips

\[ \langle v, (cp, s) \rangle \in \mathcal{A} \]

Buses (EVs and ICEVs)

Charging Slots

Assign Transit Trips to Buses

Assign EVs to Charging Slots

\[ S \quad S \quad S \]

\[ 0 \quad 1 \quad 2 \]

\[ S \quad S \quad S \]

\[ 21 \quad 22 \quad 23 \]
Model

Objective

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

\[
\min_{A} \sum_{v \in V : M_v \in M} K_{\text{gas}} \cdot e(A, v, s) + \sum_{v \in V : M_v \in M} K_{\text{elec}} \cdot e(A, v, s)\]
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

Update the energy cost matrix

Assign the selected trip to the selected bus

Feasible trip exists

STOP

No more feasible trips/All trips assigned

All trips assigned

STOP

START
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: $(\alpha \cdot (x_{start} - x_{end}), \alpha \cdot (x_{end} - x_{start}))$
- Motivation for factoring in wait-time
  - Increases bus utilization.
  - Decreases longer waiting period.
Simulated Annealing

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

Lower the temperature

Is temperature greater than threshold?

Generate Random Neighbor for current solution

Better than current solution?

Greater than random probability?

Accept Random Neighbor 
And update the current solution

Compute the acceptance probability

START

STOP

No

Yes

No

Yes

Yes

No
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/
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/
Results
Energy Prediction

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

Smaller Problem Instances

[Graph showing time [seconds] vs. number of bus lines for different algorithms: Integer Program, Simulated Anneal, Greedy Algorithm.]

[Graph showing energy cost vs. number of bus lines for Simulated Annealing and Greedy Algorithm.]
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 CO$_2$ 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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