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

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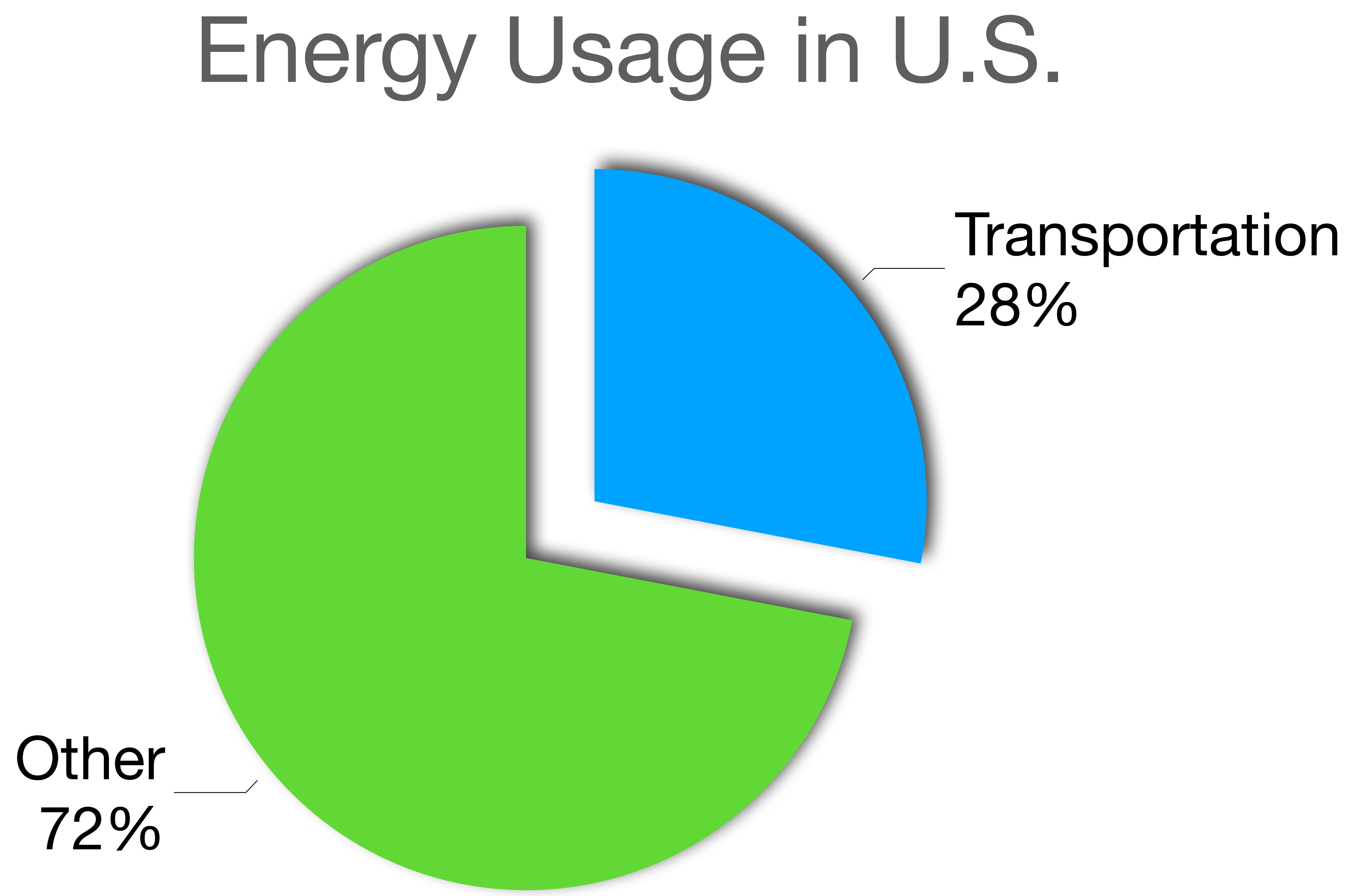
Introduction

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

- In U.S., public transportation is responsible for **21.1** million metric tons of CO_2 emission [2]



[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 !

Hybrid Bus

Diesel Bus

Electric Bus

Introduction

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

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 ?

- **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.

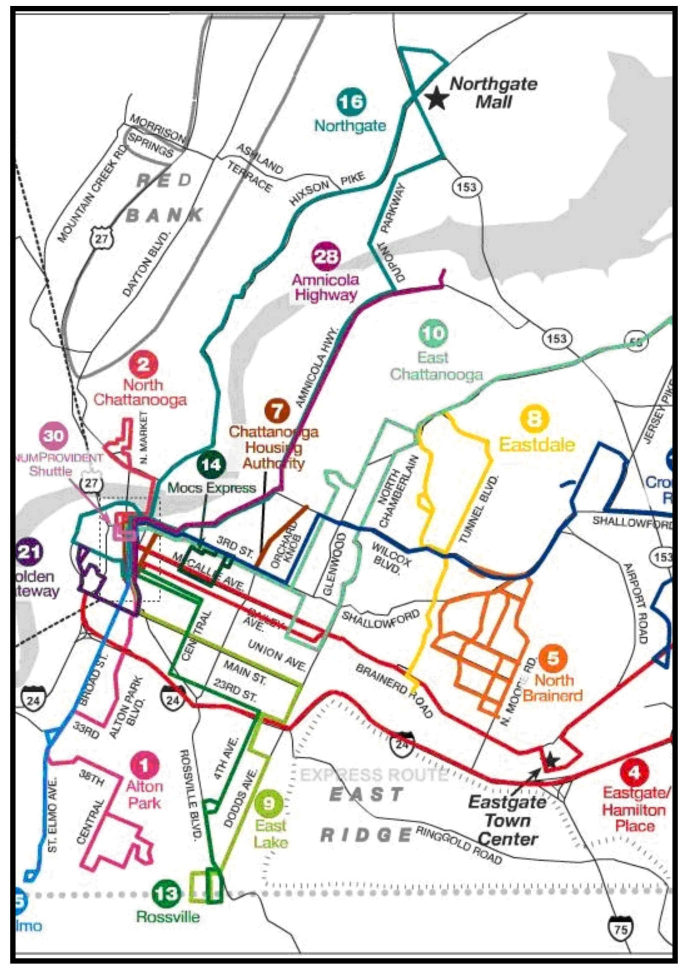
Model

Vehicles - ($\mathscr{V}$)

- Electric Vehicles ($v \in \mathscr{V} \wedge M_v \in \mathscr{M}^{elec}$)
  - Limited Battery Capacity (C_m)
  - Needs to charge within the day
- ICE Vehicles ($v \in \mathscr{V} \wedge M_v \in \mathscr{M}^{gas}$)
  - Can serve throughout the day without refueling

Transit Trips - ($\mathscr{T}$)

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



Model

Charging Slots ($\mathscr{C}$)

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

Day is divided into 24 slots

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

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

$$\forall t_1, t_2 \in \mathcal{T};\ t_1^{\text{start}} \leq t_2^{\text{start}};\ \langle v, t_1 \rangle \in \mathcal{A};\ \langle v, t_2 \rangle \in \mathcal{A} : t_1^{\text{end}} + D(t_1^{\text{destination}}, t_2^{\text{origin}}) \leq t_2^{\text{start}}$$

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

$$\forall v \in \mathcal{V}, \forall s \in \mathcal{S} :\ 0 < r(\mathcal{A}, v, s) - e(\mathcal{A}, v, s) \leq C_{M_v}$$

Model

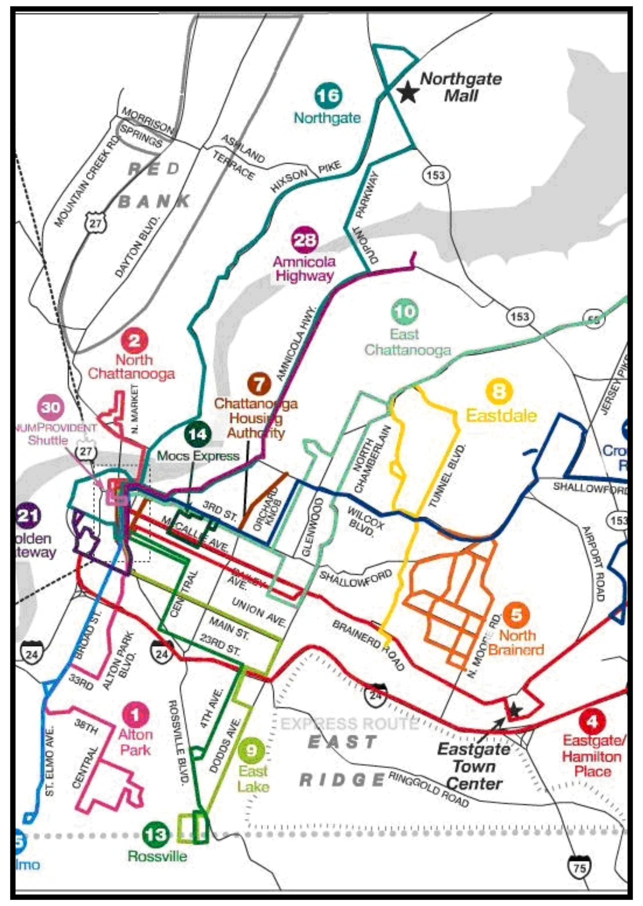
Solution Representation

$$\langle v, t \rangle \in \mathscr{A} \qquad\qquad \langle v, (cp, s) \rangle \in \mathscr{A}$$

Transit Trips ⟷ **Buses (EVs and ICEVs)** ⟷ **Charging Slots**

Assign Transit Trips to Buses

Assign EVs to Charging Slots



Model

Objective

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

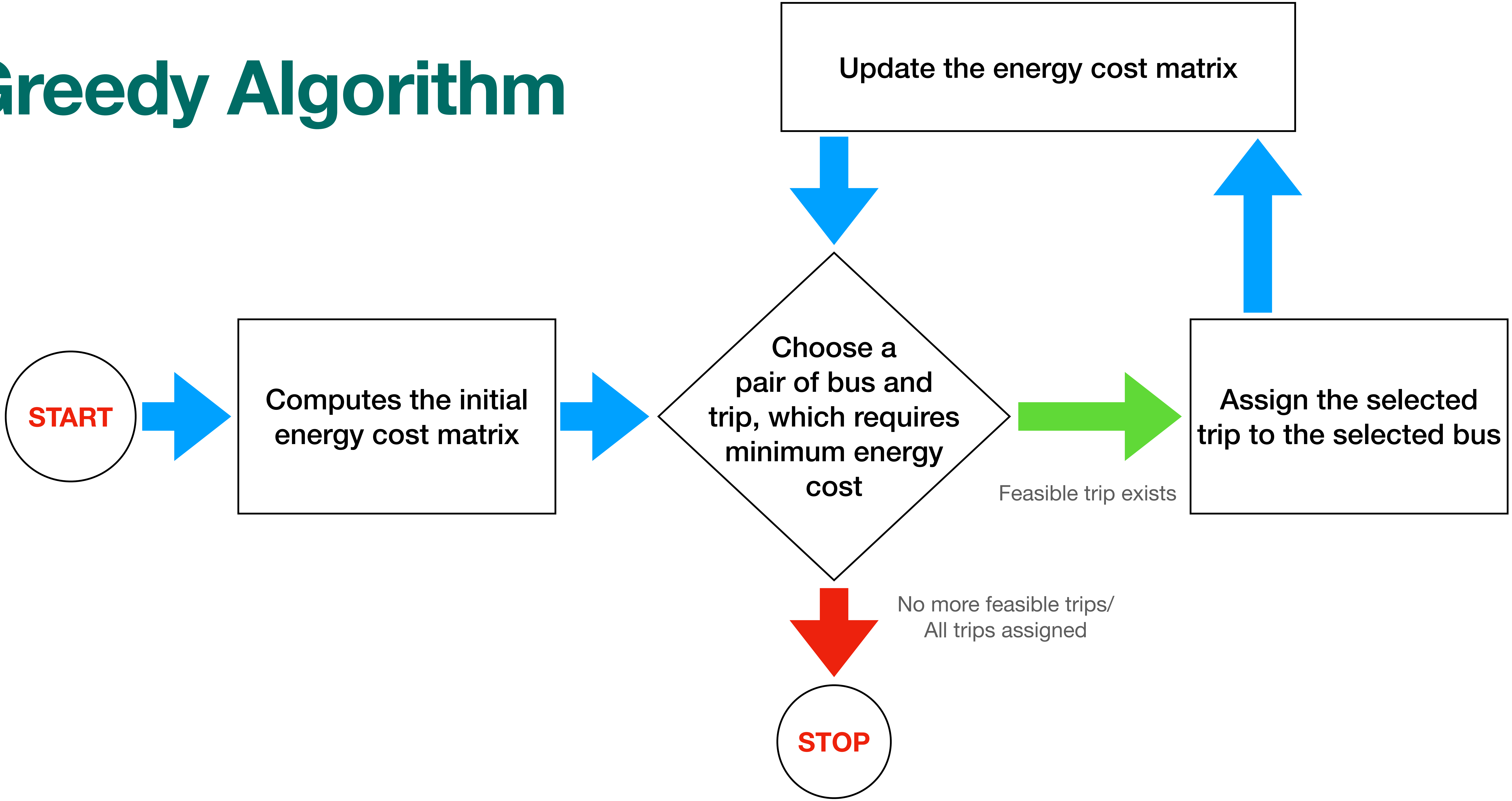
$$\min_{\mathscr{A}} \sum_{v \in \mathscr{V} : M_v \in \mathscr{M}^{\text{gas}}} K^{\text{gas}} \cdot e(\mathscr{A}, v, s_\infty) + \sum_{v \in \mathscr{V} : M_v \in \mathscr{M}^{\text{elec}}} K^{\text{elec}} \cdot e(\mathscr{A}, v, s_\infty)$$

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



Greedy Algorithm

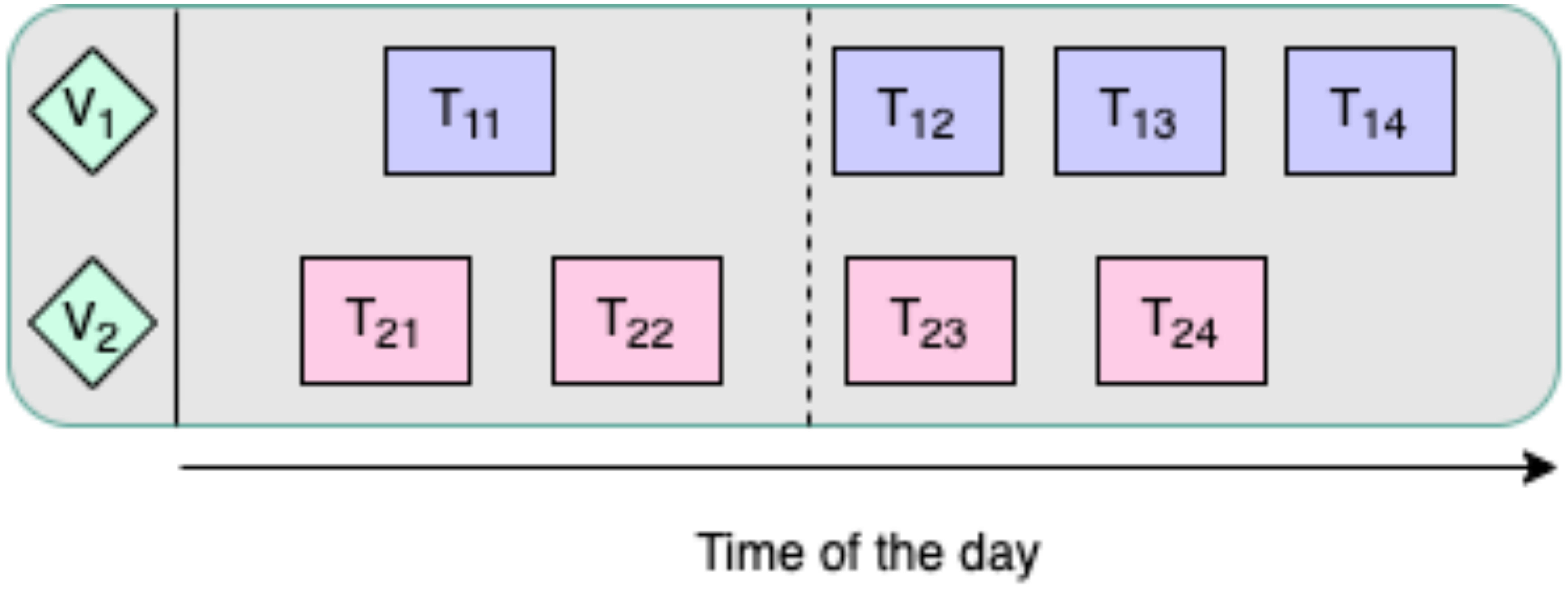
Biased Cost

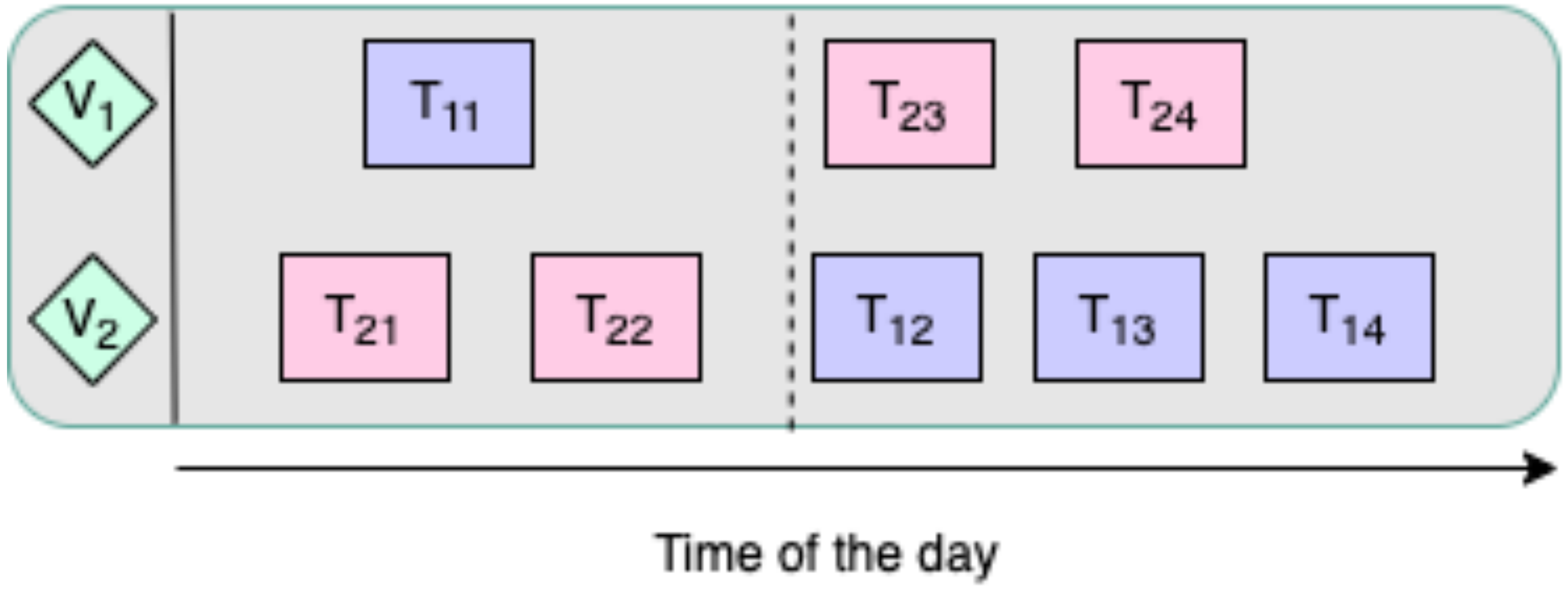
- Energy costs for serving transit trip: $E(v, x)$
- Energy costs associated with non-service trip: $(E(v, m_{prev}), E(v, m_{next}))$
- Wait-time between consecutive trips: $(\alpha \cdot (x^{start} - x^{end}_{prev}), \alpha \cdot (x^{end} - x^{start}_{next}))$
- Motivation for factoring in wait-time
  - Increases bus utilization.
  - Decreases longer waiting period.

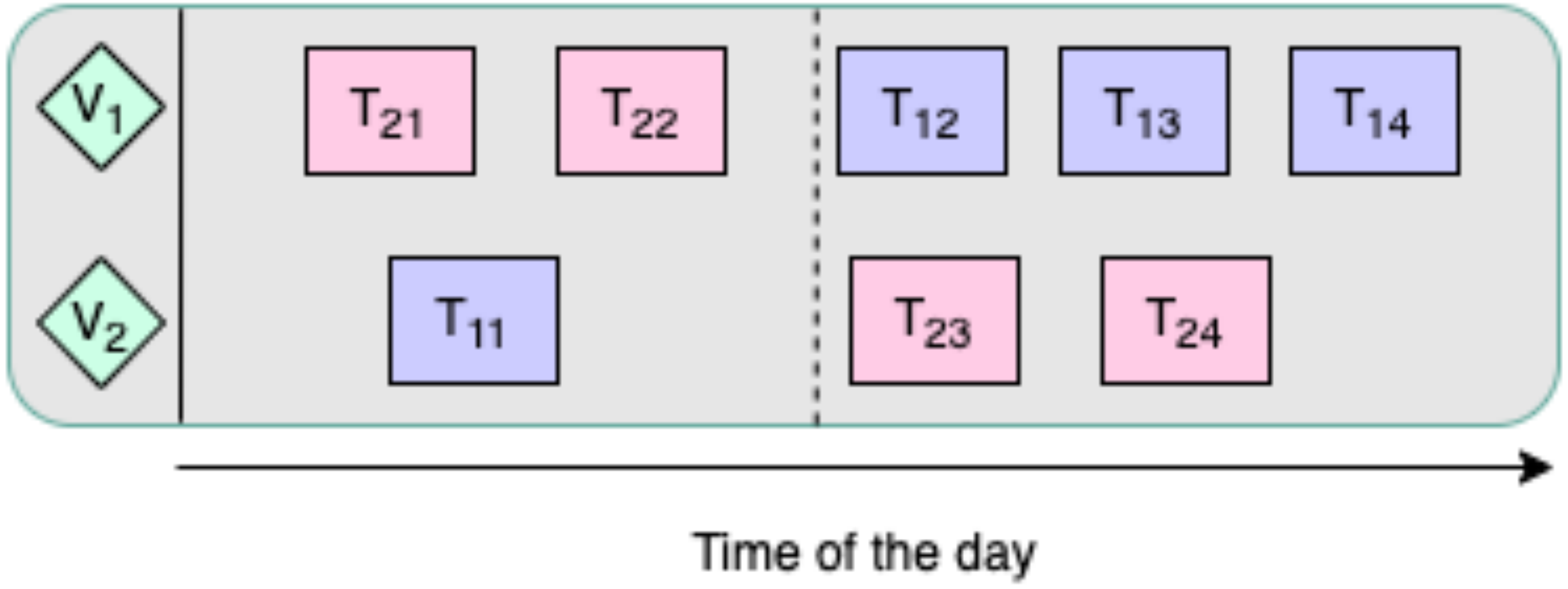
Simulated Annealing

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

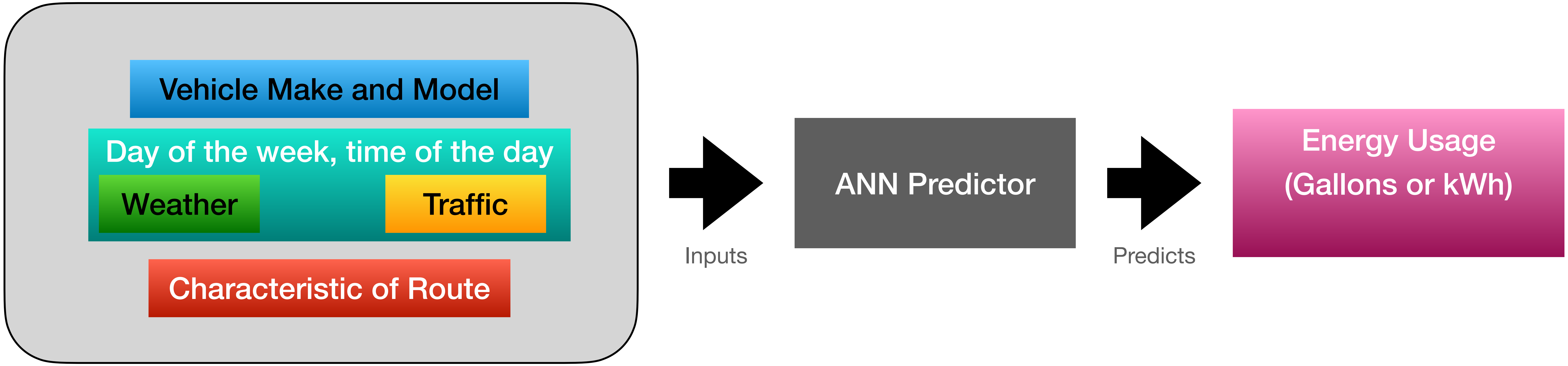
- Obtain real data from sensors
  - Vehicle location
  - Energy usages
- Obtain weather data from DarkSky
- Obtain traffic data from HERE maps

The data and code are available at https://smarttransit.ai/

Results

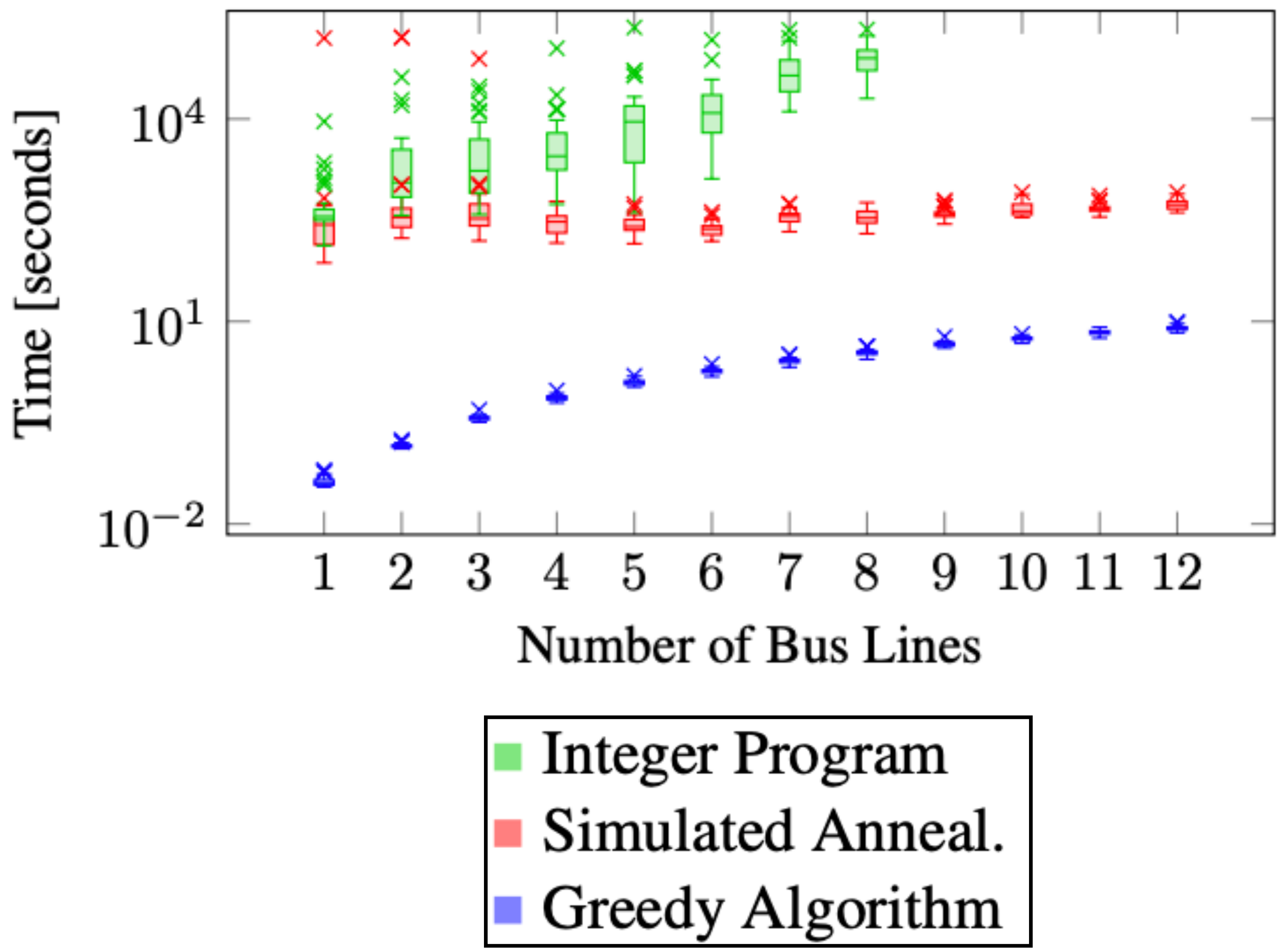
Energy Prediction

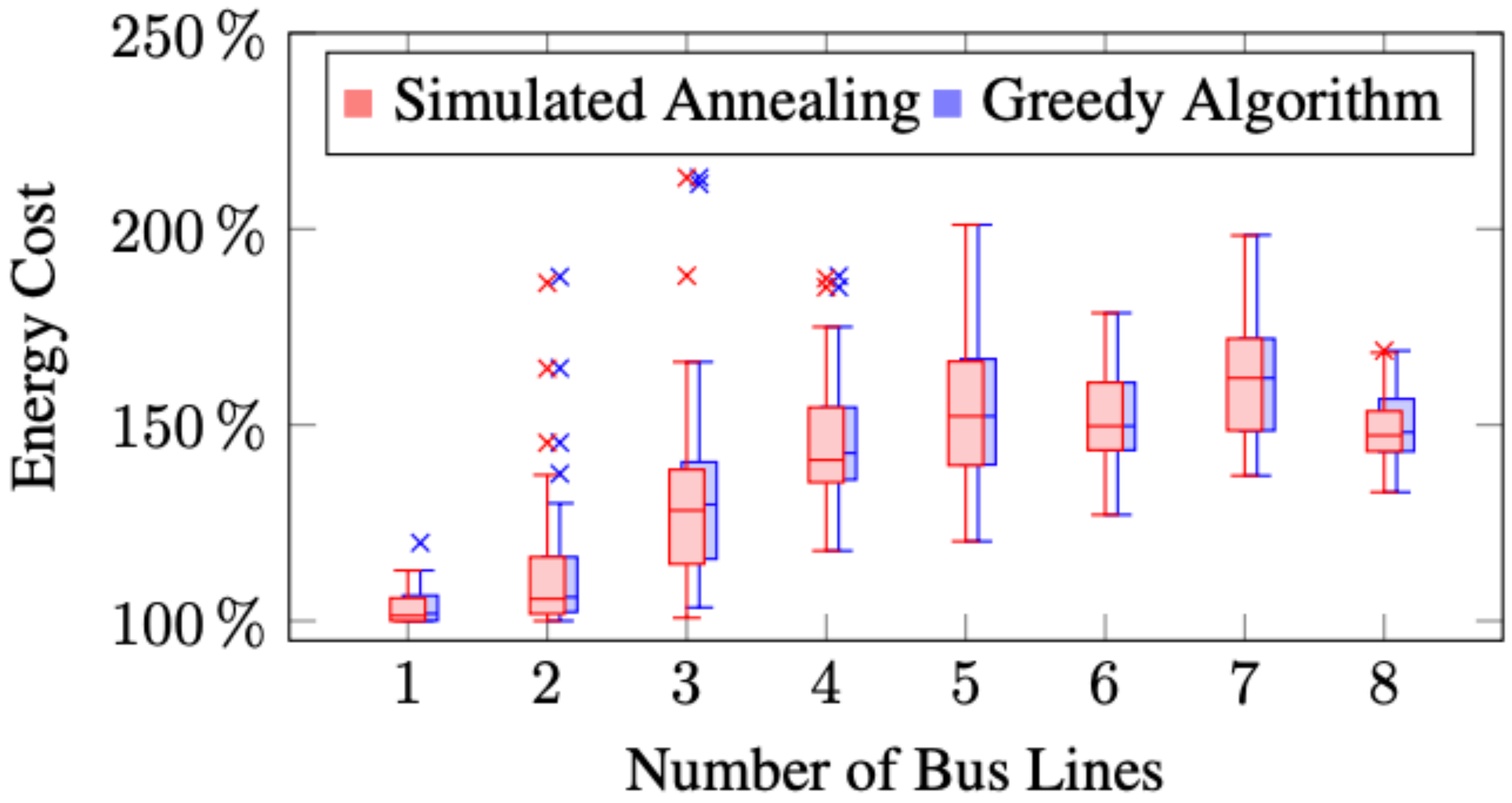
- We use Artificial Neural Network (ANN) to predict energy estimates from collected data



Results

Smaller Problem Instances

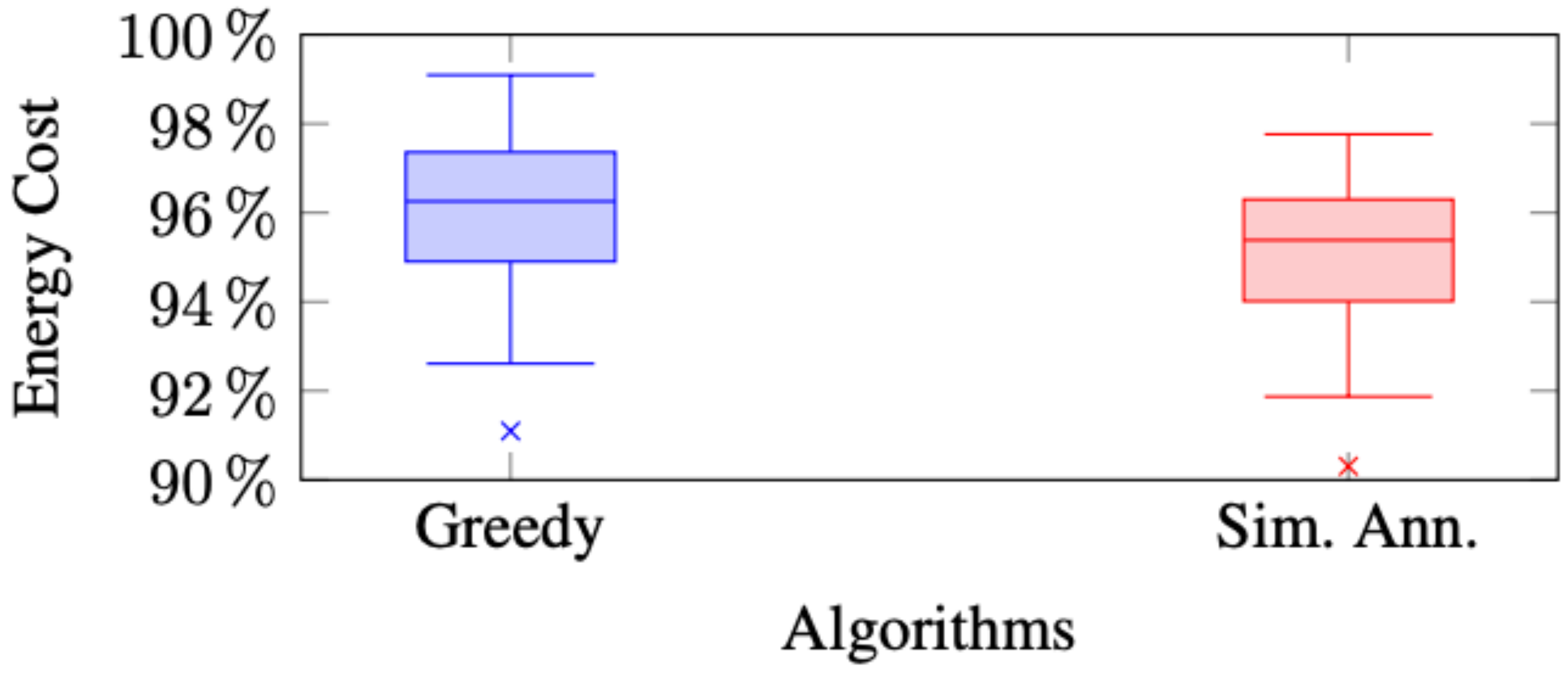




Results

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 !

Q & A

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