Pooled Rideshare, Human Factors, and the Reconsideration of Mode Shifting

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Proactive Assignment Strategy Study

Project Objectives

Primary Objective:

Increase the usage of pooled ridesharing and decrease emissions through understanding and improving rideshare offerings.

Teams and Expertise:

Project partners like JD Power and ANL provide valuable information from different perspectives.

Topics for Today:

- **Survey**
- **Choice Model**
- **Assignment Strategy**
- **Fleet Results**
- **Financial Results**
- **Mode Choice Results**

Fleet Control Based Strategies

- Assignment
- Repositioning

Vehicle and Programmatic Designs

- In-built safety features
- Matching, advertising, incentives

Human Factors Team

- Qualitative understanding of influential factors

Engineering Team

- Quantitative impacts of addressing human factors through behavioral modeling and design

Human Factors Survey

- Survey issued to 2,884 Americans in a nationally representative sample
- Stated choice question asked respondents to choose between pooled and solo
- Please see poster presentation TRBAM-24-06021

Example Question

Category	Option I	Option II
Trip Purpose/Time of Day	Urgent, Night	
Rideshare Type	Personal	Pooled
Travel Time	28	39-51
Trip Cost	22.12	12.61
Walking Distance	N/A	¼ Mile (about 6 mins)
Potential Additional Passengers	N/A	1 (Pre-screened)
Vehicle Type	Large (6 Passengers, 5 bags)	

Survey Sections

I. *Your Transportation Needs*

II. *Willingness to Consider*

III. *Pooled/Solo Stated Choice*

IV. *Most Important Factors*

V. *Demographics*

PR Choice Model

PR Choice Model

- Determines agent behavior when presented with alternative between PR and solo ride, Mixed Logit
- WTP formulation determines the discount offer based on calculated delay

PR Choice Model Factors	
Demographic Factors	**Trip Factors**
Income	Trip Purpose (ex. Urgent/Leisure)
Gender	Time of Day
Age	Vehicle Size
Education	Trip Length
Employment	# of Additional Passengers
Zone Type (ex. Urban, Rural)	Walking Time to Pickup Area
# of Children	Passengers Safety Screened
# of Vehicles in Household	
Previous Experience with PR	
Typical Transportation Mode	

WTP Required Discount Calculation

$$c = d * \left(\frac{u_d}{u_c} + h * \frac{u_{hd}}{u_c} \right)$$

where

c - % cost saving

d - % delay

h - the trip urgency (binary, 1 is urgent)

u_d, u_c, u_{hd}- utilities for delay, cost, urgency/delay interaction

PR Choice Calculation

$$u = u_d * d + u_g * g + u_a * a + [\dots] + u_n * n$$

$$p = \frac{e^u}{1 + e^u}$$

Random draw from uniform distribution for choice

Heuristic PR Assignment with Discount

Rideshare Request Submission → PR Choice Model → Nearest Vehicle Search → Selection → Assignment

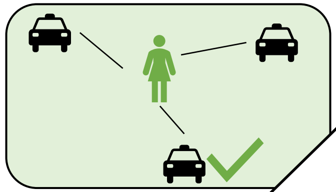
Fixed rate discounts offered for improving pooling

Demographics

Trip attributes

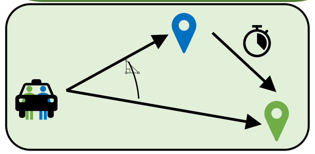
Zonal average approximation to predict trip attribute values prior to assignment

Nearest Vehicle Search
- Wait Time Filtering
- On-board Passenger Check

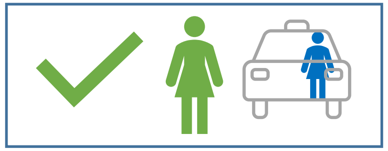


Selection
- Angular Incidence Calculation
- Routing Calculation
- Routing Delay Calculation
- Selection of closest satisfactory vehicle

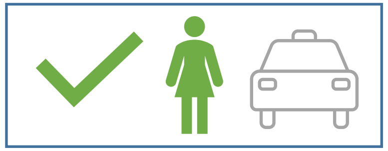
Routing Delay = Routed Solo Travel Time – Routed Pooled Travel Time



Assignment



Pooled ride

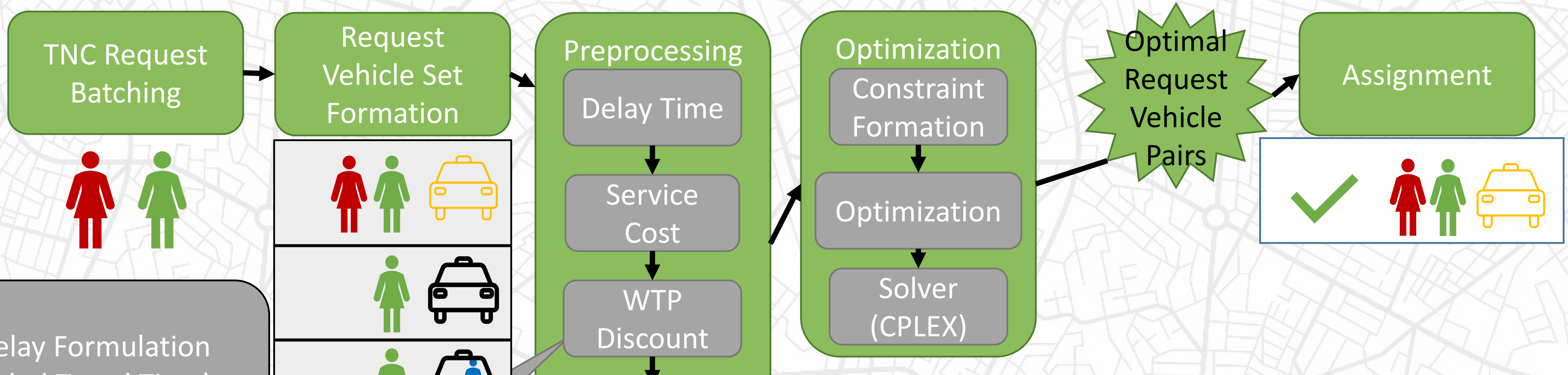


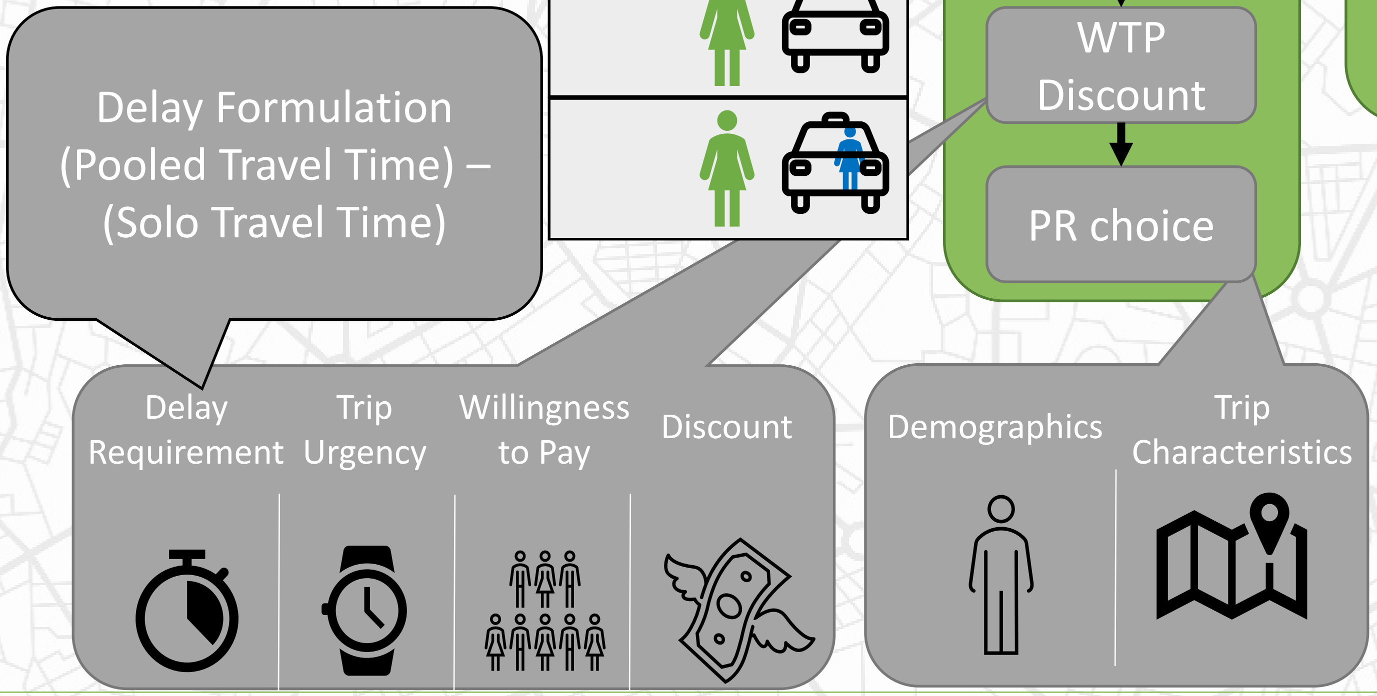
Solo ride

Heuristic Assignment:
- PR choice based on zonal average predicted trip attributes
- Heuristic nearest vehicle search is used for vehicle assignment

Strategy Notes:
- Simplistic formulation is robust and behaves predictably
- Heuristic strategy is time-efficient but could not achieve the best performance in maximizing the factor effects
- High sensitivity to density

Optimization Discount Assignment Strategy





Strategic Goal

- More realistic PR choice sequence
- Targeting increasing system efficiency with active management of discounting/subsidy
- Non-heuristic with practical time of execution for deployment

Core Optimization

Objective

- Maximize gross profit as the linear combination of profits from solo requests and pooled requests, both in parallel and sequential form

Objective Function:

$$\max \sum_{\substack{i \in R_v^\rho, r \in R, \\ v \in V, \exists i=\{r\}}} G_{rv}^\xi x_{iv} + \sum_{\substack{i \in P_v^\rho \cup R_v^\rho, \\ v \in V, \exists |i|>1}} [B_{iv} G_{iv}^\rho + (1 - B_{iv}) \sum_{r \in i} G_{rv}^\xi] x_{iv}$$

Solo Revenue	Combined Revenue	Solo revenue

Request Assignment Constraint:

$$\sum_{\substack{i \in P_v^\rho \cup R_v^\rho, \\ v \in V_r, \exists r \in i}} x_{iv} \leq 1 \ \forall r \in R,$$

$$if\ V_r \neq 0$$

Vehicle Assignment Constraint:

$$\sum_{i \in R_v^\rho \cup P_v^\rho} x_{iv} \leq 1 \ \forall v \in V$$

Capacity Constraint:

$$\sum_{i \in R_v^\rho \cup P_v^\rho} N_i x_{iv} \leq S_v \quad \forall v \in V$$

Variable	Definition
R	Set of all individual requests r
V	Set of all individual vehicles v
R_v^ρ	Subset of feasible pooled requests i that can be served by v
P_v^ρ	Subset of feasible solo requests that can be served by v
I	Set of combinations of requests $\forall r \in R$ such that $\|i\| > 1$ is pooled and $\|i\| = 1$ is solo
B_{iv}	Binary, 1 if requests in i served by v overlap and 0 otherwise
G_{iv}^ρ	Revenue of servicing combine trips i with vehicle v
G_{rv}^ξ	Revenue of servicing solo trip r with vehicle v
N_i	Sum of riders in requests r in request set i
S_v	Available seats in v
X_{iv}	Binary, 1 if request set i assigned to vehicle v

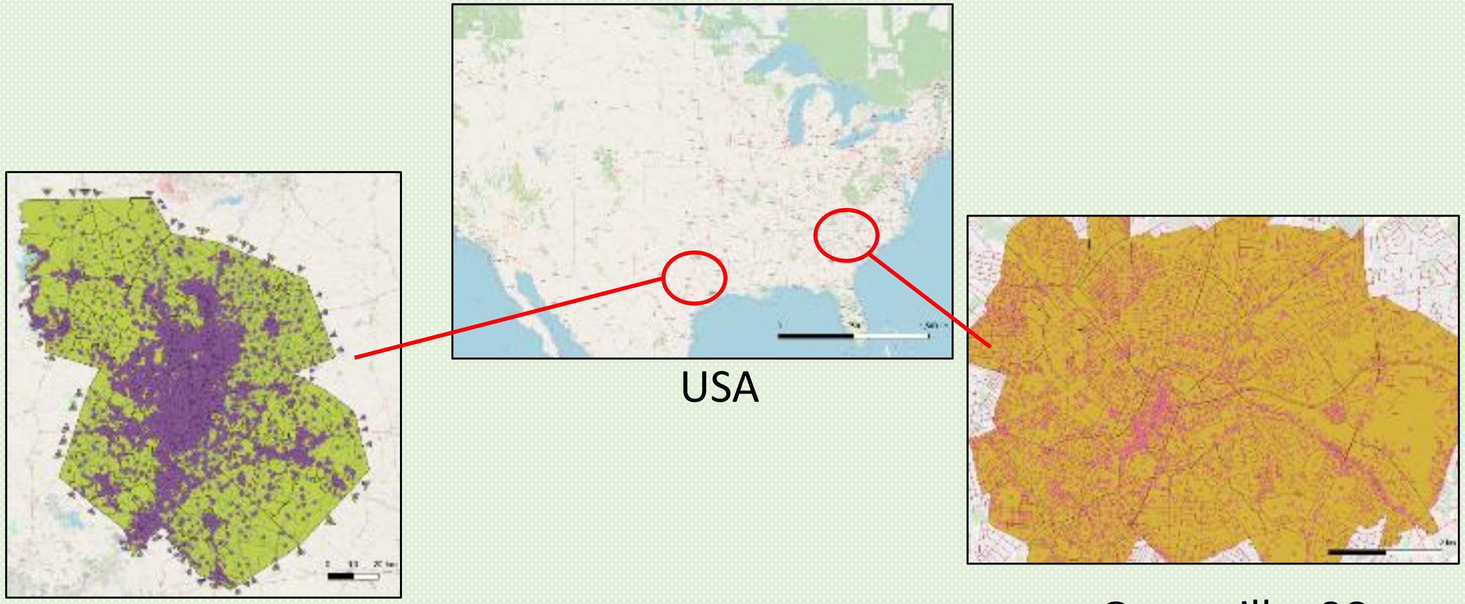
Mixed Integer Linear Programming (MILP)

- Fast enough to use real time
- Optimality
- Batching, sensitive to larger action spaces

Numerical Experiments

- POLARIS, agent-based simulation used for testing
- Heuristic based strategy used for comparison
  - Heuristic matches nearest vehicle with pooling pre-approval

Regional Models



USA

Austin, TX

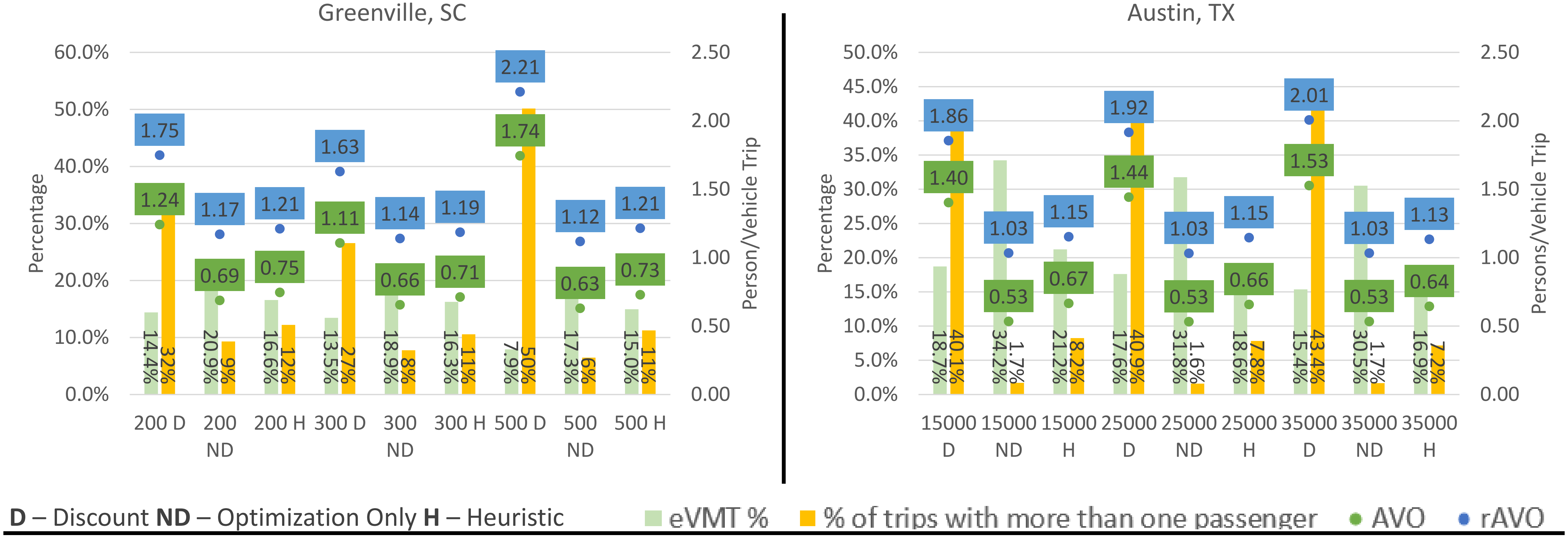
Greenville, SC

Cities	Fleet Sizes	Strategy
Greenville, SC (GSC)	200, 300, 500	Heuristic (H), Discount Based (D), Optimization Only (ND)
Austin, TX (ATX)	15K, 25K, 35K	Heuristic (H), Discount Based (D), Optimization Only (ND)

Test Cases

- Discount runs executed first
- Effective overall discount rate calculated
- Heuristic strategy run for each fleet size with calculated homogeneous discount rate
- Supply Demand Mismatch Characteristics:
  - GVL – Excess Supply, ATX- Excess Demand

Fleet Level Results



D – Discount **ND** – Optimization Only **H** – Heuristic

Conclusions: Discount strategy **significantly improves eVMT, Trip Pooling, rAVO, and AVO** in both regions.

eVMT: ↓7.1% GSC, ↓2.5% ATX **Trip Pooling(raw %):** ↑ 39% GSC, ↑ 36% ATX

AVO: ↑ 1.01 persons/trip GSC, ↑ 0.89 persons/trip ATX **rAVO:** ↑ 1.00 persons/trip GSC, ↑ 0.88 persons/trip ATX

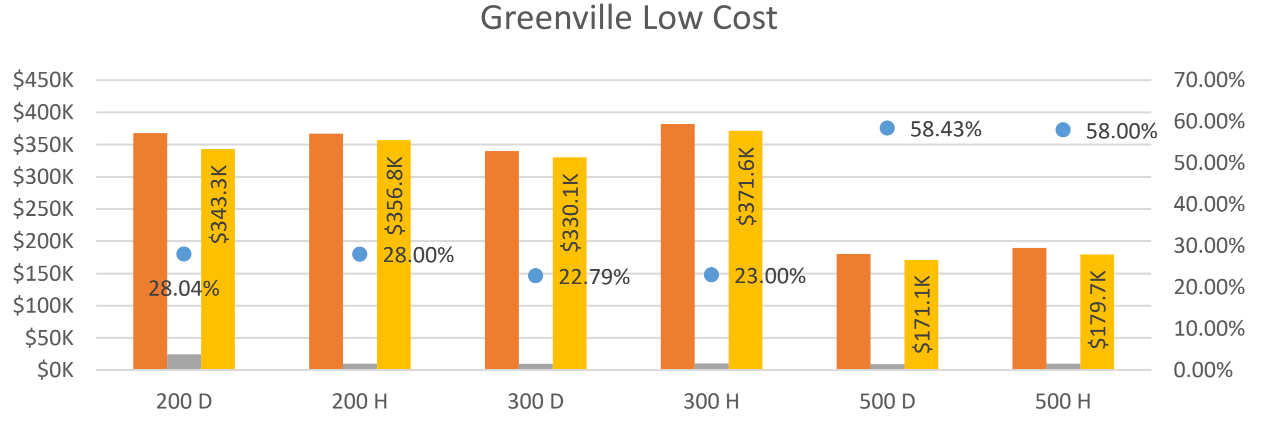
Financial Calculations

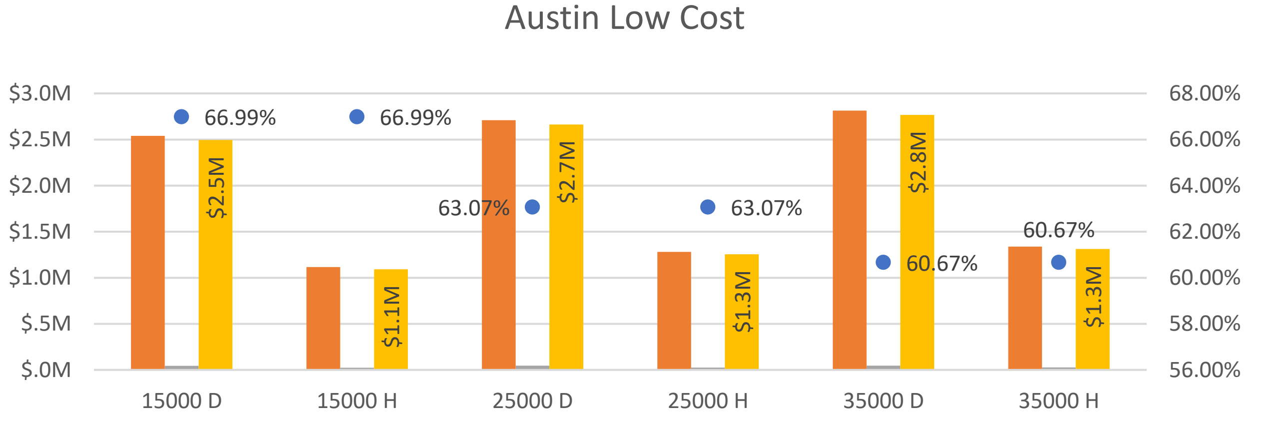
- Fare Calculations
  - Fare model calibrated from Chicago TNC Dataset (2023)
    - $f = b + milage * b_{mile} + time * b_{min}$
- Revenue
  - $r = f - d_r * f$
- Assumptions
  - Fare calculated on experienced trip (future work to address)
  - Driver costs not considered

Model Attribute	Variable	Value
Fare	f	-
Intercept	b	\$5.09
Per Mile Rate	b_{mile}	\$0.89/mile
Per Minute Rate	b_{min}	\$0.29/min
Number of observations	-	11,973,880
R^2	-	0.67
Ride Discount	d_r	-
Revenue	r	-
Per Mile Operating Cost	-	High: \$0.80/mile Low: \$0.50/mile [1]

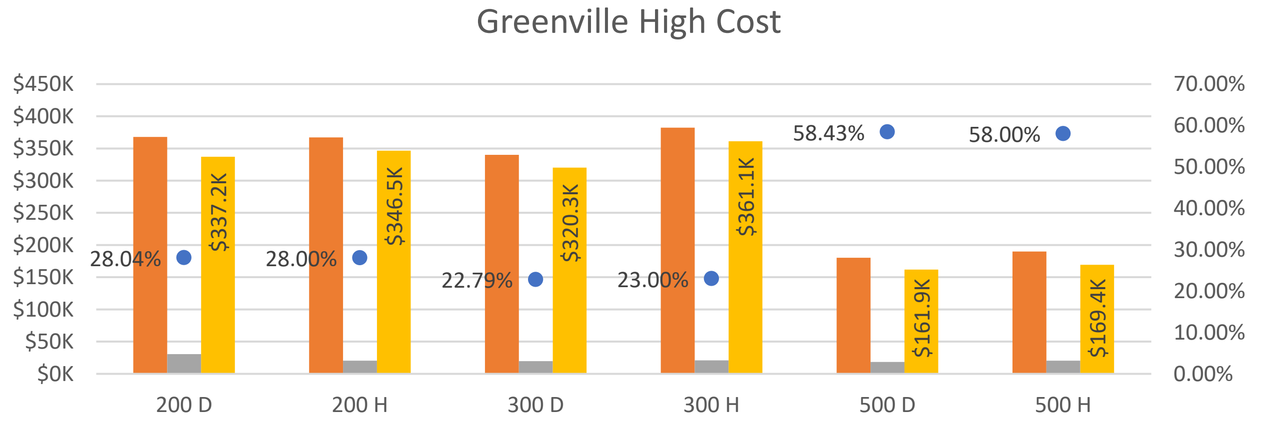
[1] J. Farhan and T. D. Chen, "Impact of ridesharing on operational efficiency of shared autonomous electric vehicle fleet," *Transportation Research Part C: Emerging Technologies*, vol. 93, pp. 310–321, Aug. 2018, doi: 10.1016/j.trc.2018.04.022.

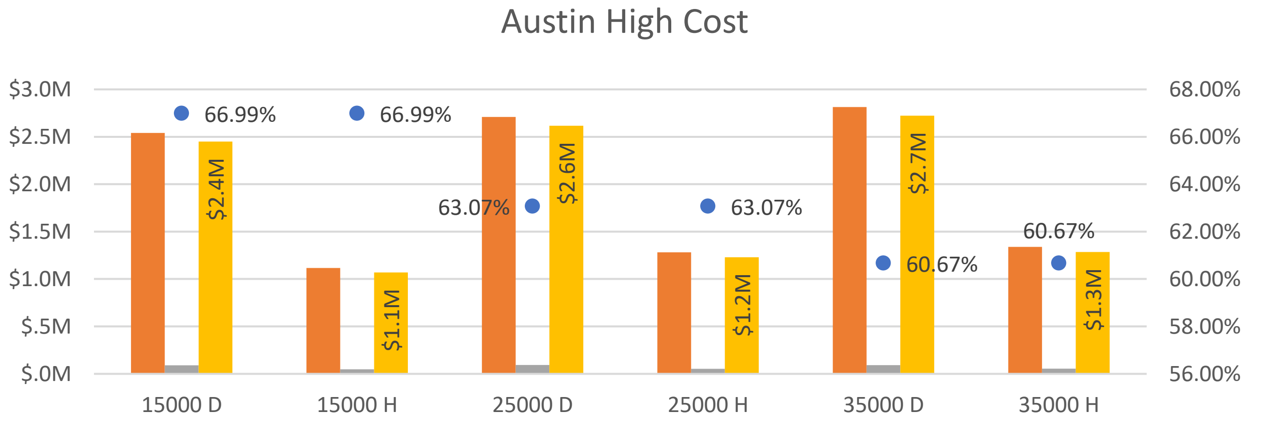
Financial Results





Total Revenue Total Estimated Operating Cost Total Estimated Profit Average Effective Discount Rate



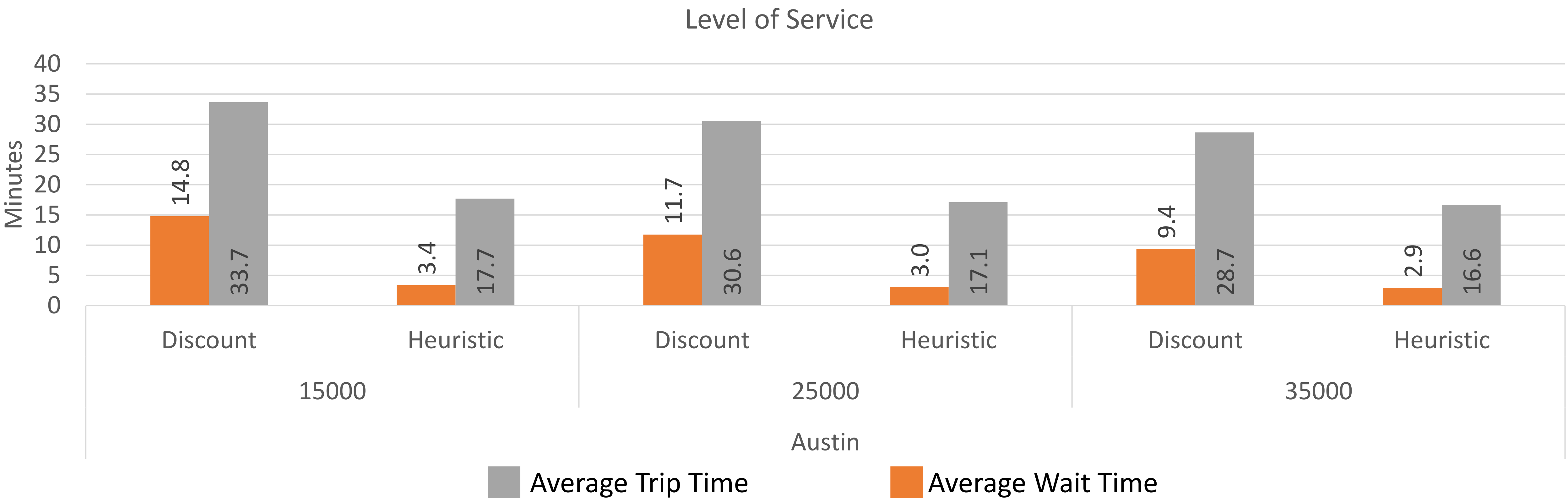


Conclusions: Discount strategy **improves profitability** significantly in Austin, but decreases slightly in Greenville, likely due to supply/demand.

Max Profit (Low Cost - Raw): ↓ $13.4K GSC, ↑ $1.40M ATX **Max Profit(Low Cost - %):** ↓ 12% GSC, ↑ 408% ATX

Max Profit (High Cost - Raw): ↓ $40.8K GSC, ↑ $1.44M ATX **Max Profit(High Cost - %):** ↓ 11% GSC, ↑ 403% ATX

Level of Service Changes



Conclusions: Discount strategy **increases average weight time, average trip time and average fare** (before discount applied).

Average Wait Time: ↑ 11.4 min ATX **Average Travel Time:** ↑ 15.9 min ATX **Average Fare:** ↑ $5.60 ATX

Underlying shifts in demand due to sharing and handling likely contribute to increases on top of pooling.

Conclusions

Proactive Assignment

- Realistic consideration of rider behavior
- Possibility of profitability and public transportation replacement

Future work

- Autonomie Emissions Study
- Repositioning strategy LP modifications
- RL based repositioning strategy

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