Improving Commercial Vehicle Routing with Parking Information

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Introduction

Background

Commercial vehicle driver's job is challenged by increases in delivery demand, traffic delays, competition for the curb

→ carriers are striving to satisfy demand in an increasingly complex urban environment

Image source: New York City DOT

Telematics and analytics system support delivery drivers increasingly:

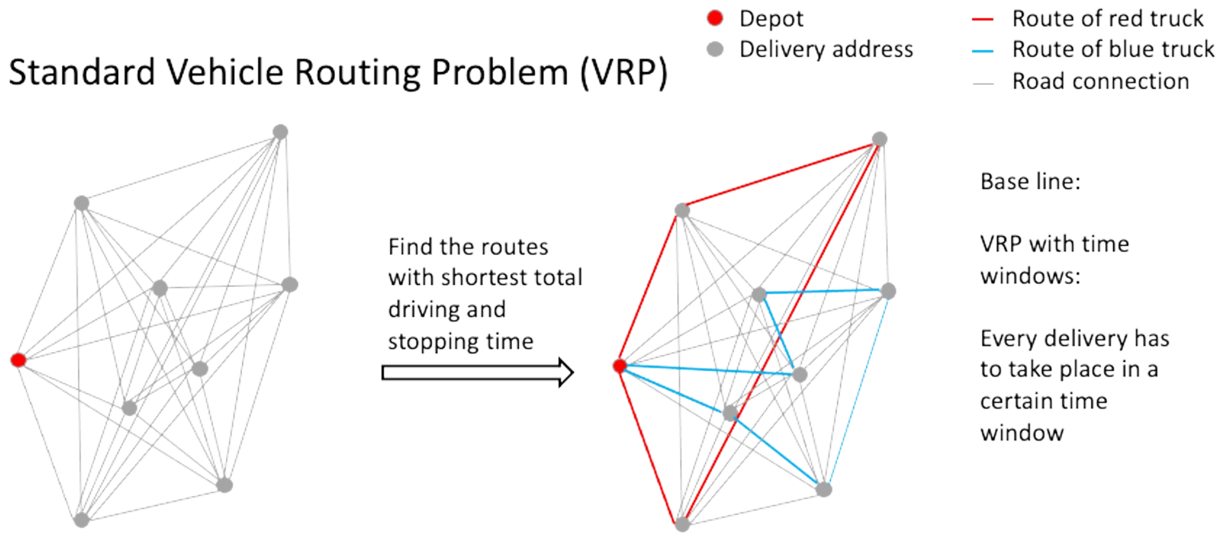
- Route planning
- Live information: traffic conditions, changes in demand, weather, accidents
- Increasingly powerful user interfaces

How do carriers route?

- Standard model as per interviews with carriers: Capacitated vehicle routing problem with time windows

INPUTS
- List of orders with delivery addresses
- Travel time matrix
- Number of vehicles with capacity

→



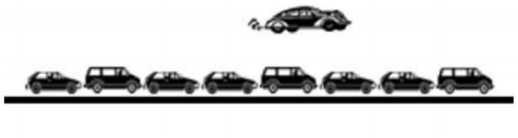
→

OUTPUTS
- Optimized route / manifest

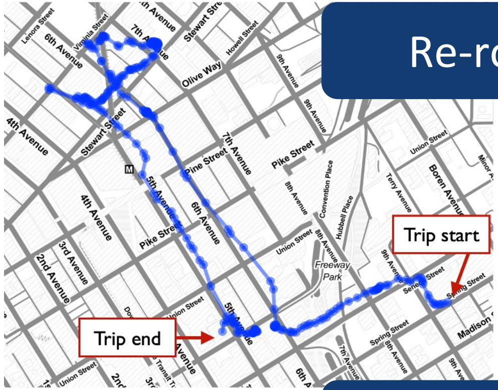
- Some routing systems use traffic information for time dependent travel times
- Parking occupancy information **not used** in scheduling/routing

What happens when parking is unavailable?

Cruising



Re-routing



Walking

Queueing

Dalla Chiara et al. (2021) Understanding urban commercial vehicle driver behaviors and decision making, Transportation research record 2675 (9), 608-619

What can we do with parking occupancy information?

Two options for using data:

Objectives

Main goal:

Evaluate the benefits of using parking occupancy information in urban deliveries

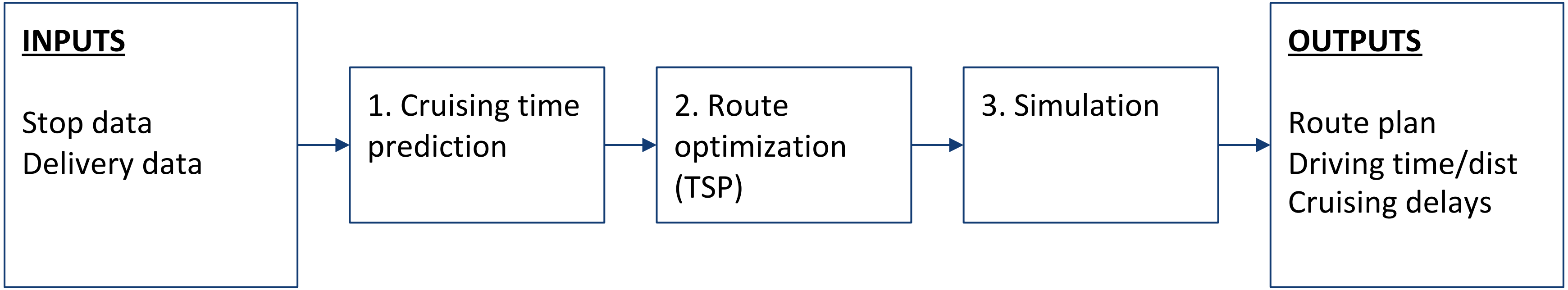
How are we going to achieve this goal?

A lack of parking occupancy information can lead to drive time delays (cruising)

Simulate the effect of incorporating cruising for parking delays into route optimization

Methodology

Overview


INPUTS
Stop data
Delivery data
1. Cruising time prediction
2. Route optimization (TSP)
3. Simulation
OUTPUTS
Route plan
Driving time/dist
Cruising delays

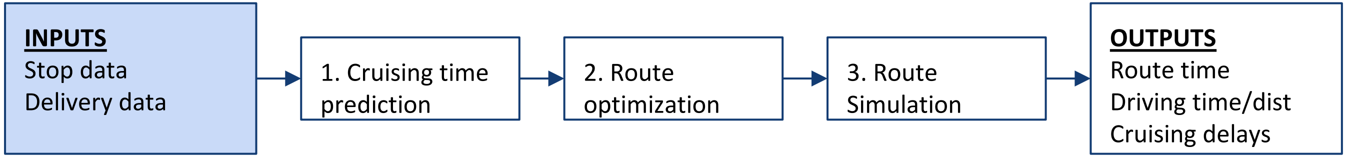
Input data (Real world)

Two data sources:

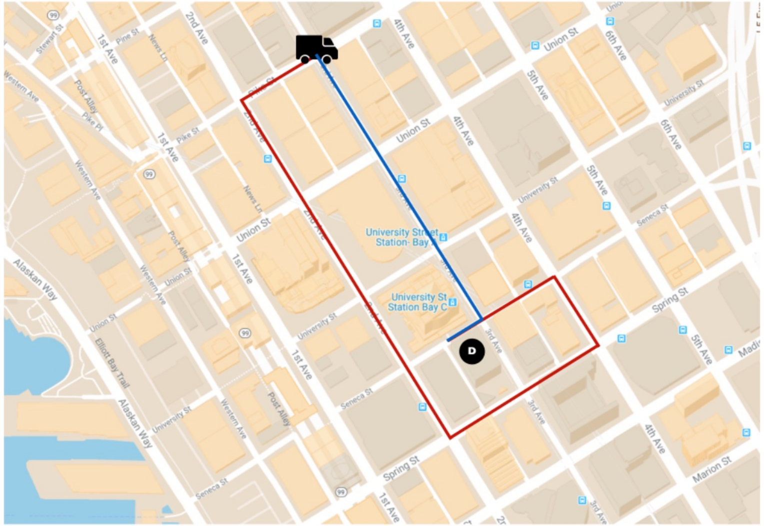
- Delivery data (from drivers' delivery device / delivery management system)
  - Customer, manifest & order details (volume, weight, delivery time window...)
  - Delivery lat/lon & time
- Stops data (from in-vehicle GPS system)
  - Stop lat/lon & time (estimated from duration near delivery addresses)
  - Stop dwell time (estimated)

Were recorded for 2 years, from a beverage distributor's carrier vehicles, performing deliveries in Seattle

- Approx. 50 drivers, 2k customers, 60k deliveries

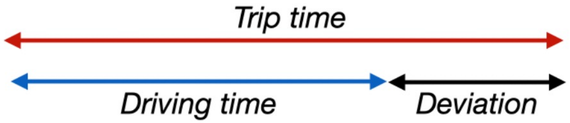


Cruising time estimation



Obtain reliable estimates of truck cruising for parking times for different data sources:

Stat	A	B
1st Qu.	0.47	1.08
Median	2.13	3.27
Mean	5.43	4.44
3rd Qu.	7.88	6.46



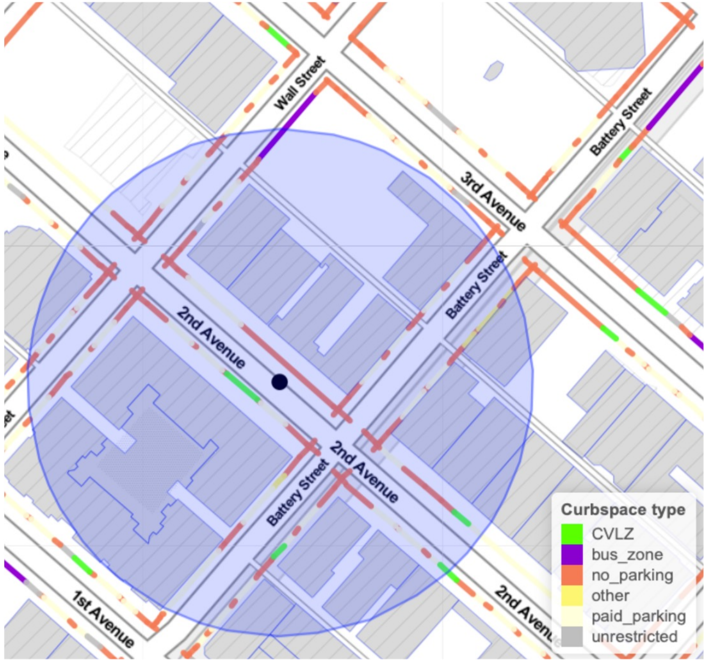
Dalla Chiara & Goodchild (2020) *Do commercial vehicles cruise for parking?* Transport Policy 97, 26-36

INPUTS
Stop data
Delivery data

→ 1. Cruising time prediction → 2. Route optimization → 3. Route Simulation →

OUTPUTS
Route time
Driving time/dist
Cruising delays

Exploring cruising delay influencers



- Parking buffers centered at trip destinations of 100 meters (330 ft.) rad.
  - Parking allocation & infrastructure
  - Built environment
  - Parking occupancy
- Other variables:
  - Time attributes
  - Activity attributes
  - Vehicle & driver attributes

INPUTS
Stop data
Delivery data

→ 1. Cruising time prediction → 2. Route optimization → 3. Route Simulation →

OUTPUTS
Route time
Driving time/dist
Cruising delays

Cruising time prediction

$$\log(trip\ time) = \beta_0 + \beta_{tt}\log(travel\ time) + \ \dots + \beta_{cvlz}\, CVLZ + \ \dots + \varepsilon$$

“Corrected” travel time matrix with cruising delays

Travel time matrix used as input to “classic” routing models

INPUTS
Stop data
Delivery data

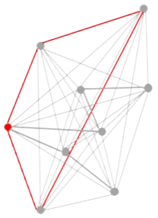
→ 1. Cruising time prediction → 2. Route optimization → 3. Route Simulation →

OUTPUTS
Route time
Driving time/dist
Cruising delays

Using cruising information to improve routes

- Update time-dependent travel time matrix with additional cruising estimation
- Show the effect of cruising predictions through two models

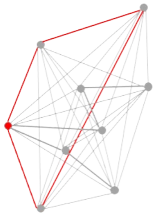
INPUTS
- List of orders, TWs, nodes
- Time-dependent travel time matrix



TD-TSP-TW with time-dependent travel times **only**

Simulate "today" -> Add estimated cruising delays to existing route plan

INPUTS
- List of orders, TWs, nodes
- Time-dependent travel and cruising time matrix



TD-TSP-TW with time-dependent travel **and** cruising times

Difference in route time shows effect of considering historic parking information

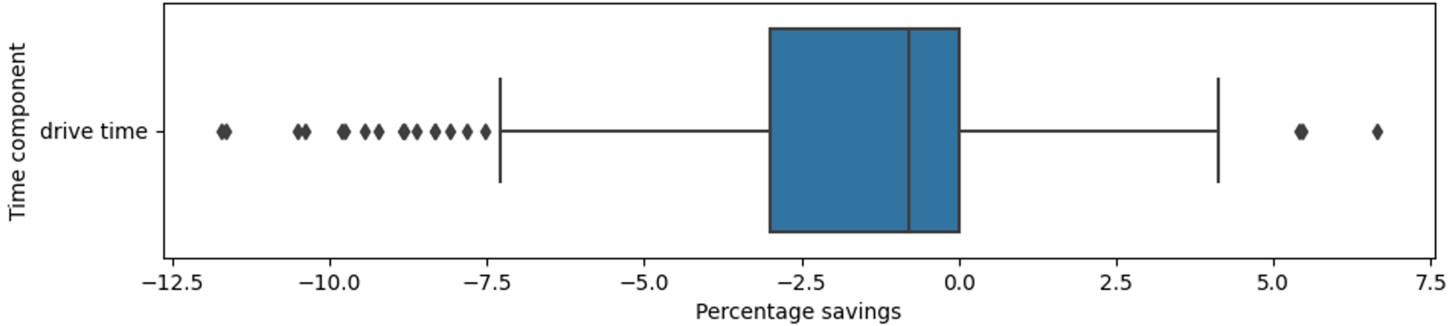
INPUTS
Stop data
Delivery data

1. Cruising time prediction → 2. Route optimization → 3. Route Simulation

OUTPUTS
Route time
Driving time/dist
Cruising delays

Results

Real World Study



- Route time savings on real world data exist, but are small (mean savings of 1.5% / 1.02 min per route)
- High number of hidden variables influence the route savings
- Interaction effects with accuracy of GPS traces

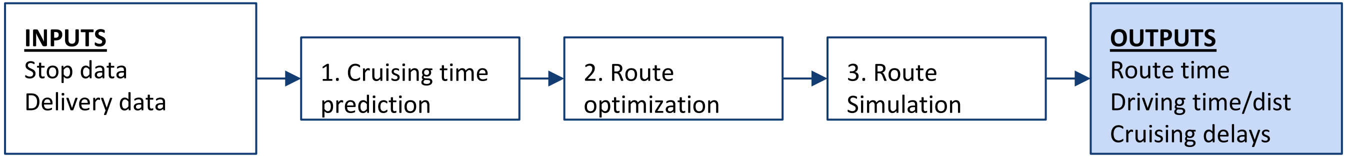
INPUTS
Stop data
Delivery data
→ 1. Cruising time prediction → 2. Route optimization → 3. Route Simulation →
OUTPUTS
Route time
Driving time/dist
Cruising delays

Synthetic Study

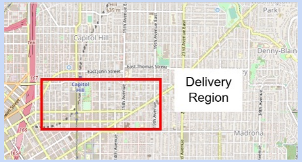
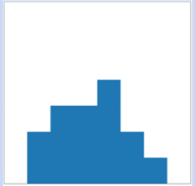
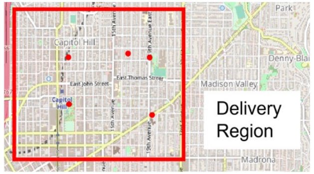
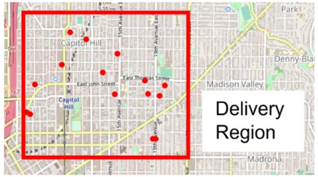
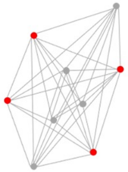
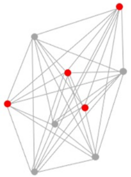
Goal: Identify route characteristics that benefit from consideration of cruising delays

Design: Full factorial 2^k experiment

Method: Delivery manifests sampled from coordinates based on varying parameters:



Synthetic Study - Parameters of Interest

Variable	Low	High	Variable	Low	High
Size of Area (a)	**1 km²** 	**4 km²** 	Variance of Cruise Time Delays (σ_{cd})	σ = 0.5 	σ = 2 
Number of Stops (n)	**5 Stops** 	**15 Stops** 	Variance of Travel Time Matrix (σ_{tt})	$\sigma = 0.35 * \sqrt{a}$ 	$\sigma = 1.5 * \sqrt{a}$ 

INPUTS
Stop data
Delivery data

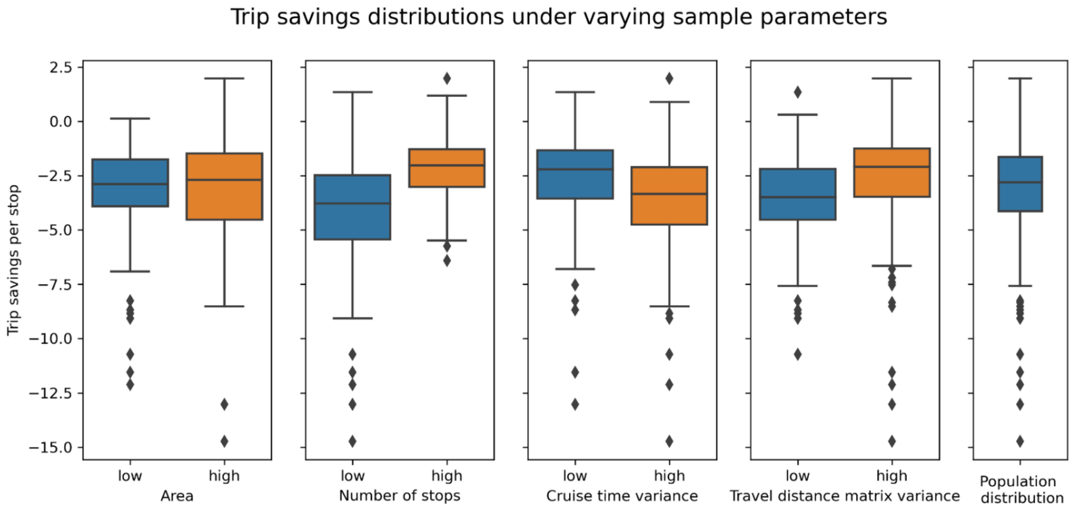
→ 1. Cruising time prediction → 2. Route optimization → 3. Route Simulation →

OUTPUTS
Route time
Driving time/dist
Cruising delays

Synthetic Study - ANOVA

Significant variables:

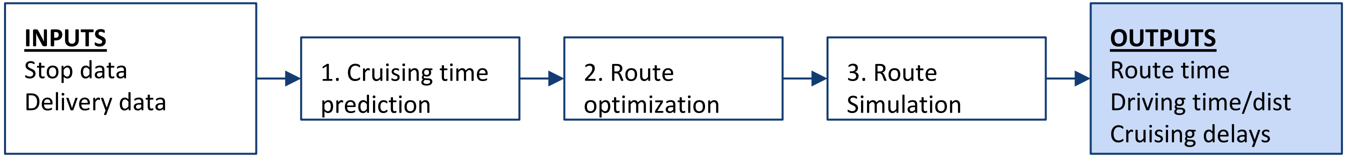
- Number of stops
- Cruising time variance
- Travel distance variance * Number of Stops



Mean saving per stop: -3.12 minutes per stop (21.6%)

Best configuration: **Few** Stops, **Homogeneous** Shape, **High** Cruising delay variance

Mean saving per stop for best configuration: -5.18 minutes per stop (39%)



Conclusions

- Yes, considering parking occupancy information in route planning **can generate** savings for route planning, but also reduces safety hazards and negative economic impacts
- Synthetic Study shows potential for savings of 21.6% in drive time per stop
  - Routes with fewer stops, concentrated shape, high cruising time variance show largest savings potential, which is common in urban environments
- This confirms similar savings observed in a pilot test from 2021 (approx. 19% drive time savings)
- Next steps in modeling can focus on improving cruising delay prediction accuracy and tweaking of meta-heuristic algorithms

Practical Implications

- Smart Cities: More transparency on parking occupancy will help carriers, cities, and the economy, as it reduces freight caused stressors to the urban environment.
    - Sequential parking sensor rollout in cities
- Online routing: Additional data feed will help enabling parking occupancy informed online routing and reduce inefficiencies with widespread benefits

Questions & Answers

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Back-Up

MP-BRKGA for TD-TSP-TW

- MP-BRKGA (Andrade et al., 2021) heuristic implicitly represents solution

Solution provided by Genetic Algorithm

Stop ID	A	B	C	D	E
Key Value	0.72	0.56	0.31	0.02	0.89

Solution re-ordered in increasing order

Stop ID	D	C	B	A	E
Key Value	0.02	0.31	0.56	0.72	0.89

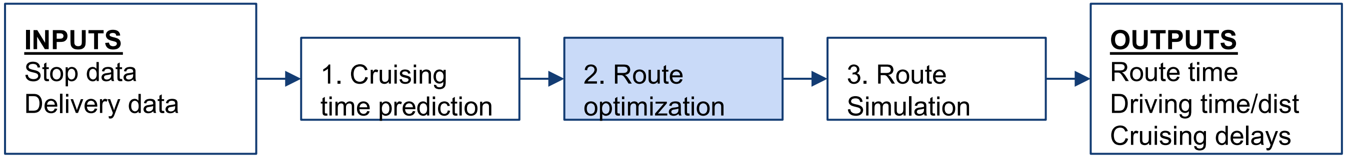
Solution translated into route plan

Depot → D → C → B → A → E → Depot

Fitness evaluated by objective function

Total route time: x min; cost incl. penalty: $\$y$

- TW constraints enforced through soft constraints
- Demonstrated strong performance for benchmarks against commercial solvers on smaller test instances



Time dependent TSP with time windows (TD-TSP-TW)

Vu et al. (2018)

$$z = \text{minimize} \sum_{((i,t),(j,t'))\in\mathcal{A}} c_{ij}(t)\, x_{((i,t),(j,t'))}$$

subject to

$$\sum_{((i,t),(j,t'))\in\mathcal{A}: i\neq j} x_{((i,t),(j,t'))} = 1, \quad \forall j \in N, \tag{1}$$

$$\sum_{((i,t),(j,t'))\in\mathcal{A}} x_{((i,t),(j,t'))} - \sum_{((j,\tilde{t}),(i,t))\in\mathcal{A}} x_{((j,\tilde{t}),(i,t))} = 0, \quad \forall (i,t) \in \mathcal{N}, i \neq 0 \tag{2}$$

$$x_{((i,t),(j,t'))} \in \{0,1\}, \quad \forall ((i,t),(j,t')) \in \mathcal{A}. \tag{3}$$

t' <= l_j
t'= max{e_j, t + tau_ij(t)}

INPUTS
Stop data
Delivery data

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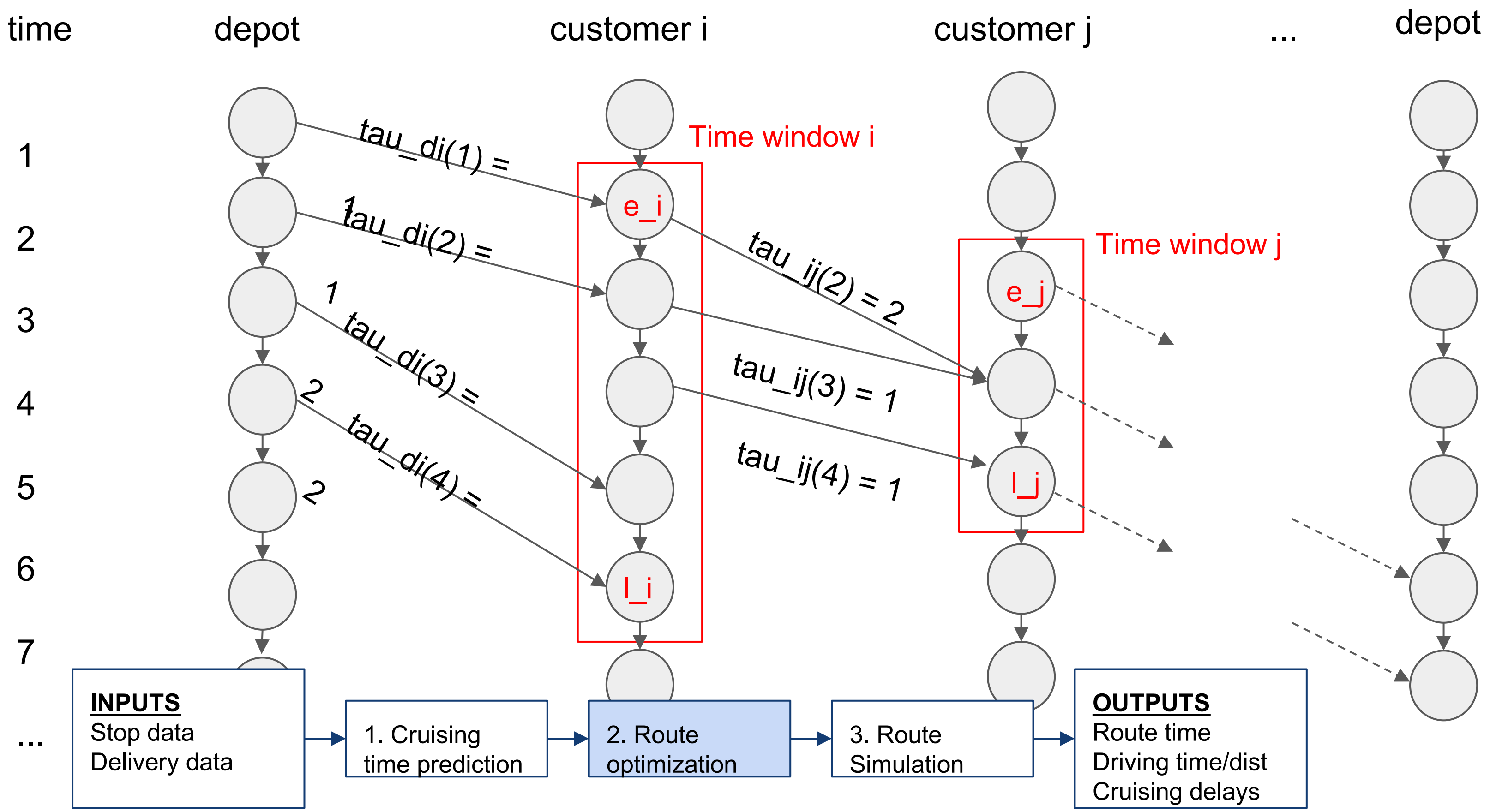
OUTPUTS
Route time
Driving time/dist
Cruising delays

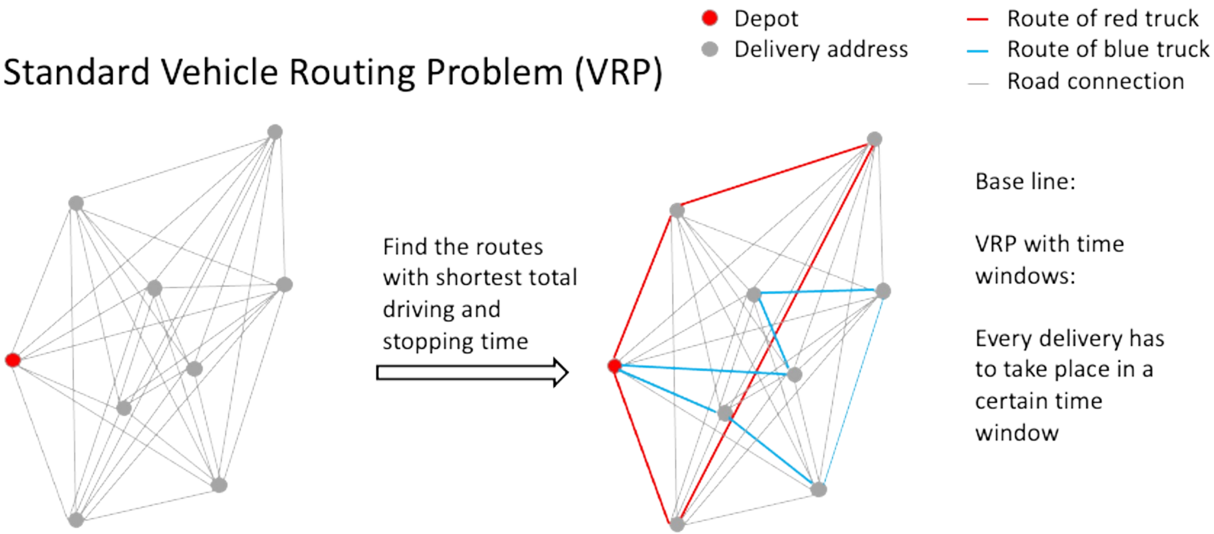
Time dependent TSP with time windows (TD-TSP-TW)



Recap: How do carriers route?

Tristan

INPUTS
- List of orders with delivery addresses
- Travel time matrix
- Number of vehicles with capacity



Base line:

VRP with time windows:

Every delivery has to take place in a certain time window

OUTPUTS
- Optimized route / manifest

INPUTS
Stop data
Delivery data

→ 1. Cruising time prediction → 2. Route optimization → 3. Route Simulation →

OUTPUTS
Route time
Driving time/dist
Cruising delays

Tristan

Simplification from VRP to TSP with time windows

What does the VRP with time windows do?

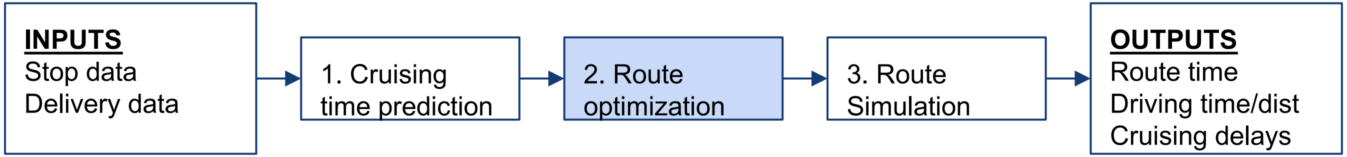
- VRP performs order allocation **and** routing simultaneously for optimal routes
- VRP with and without cruising time estimates changes travel time matrix
    - This may result in completely different order allocations and route plans

Why is that a problem?

- Difficult to isolate the effect of cruising estimates on routing

What is our solution?

- Isolate effect of cruising estimates through simplifying to TSP with time windows
    - TSP is a single-vehicle VRP and takes list of orders for a single vehicle as input and optimizes routes

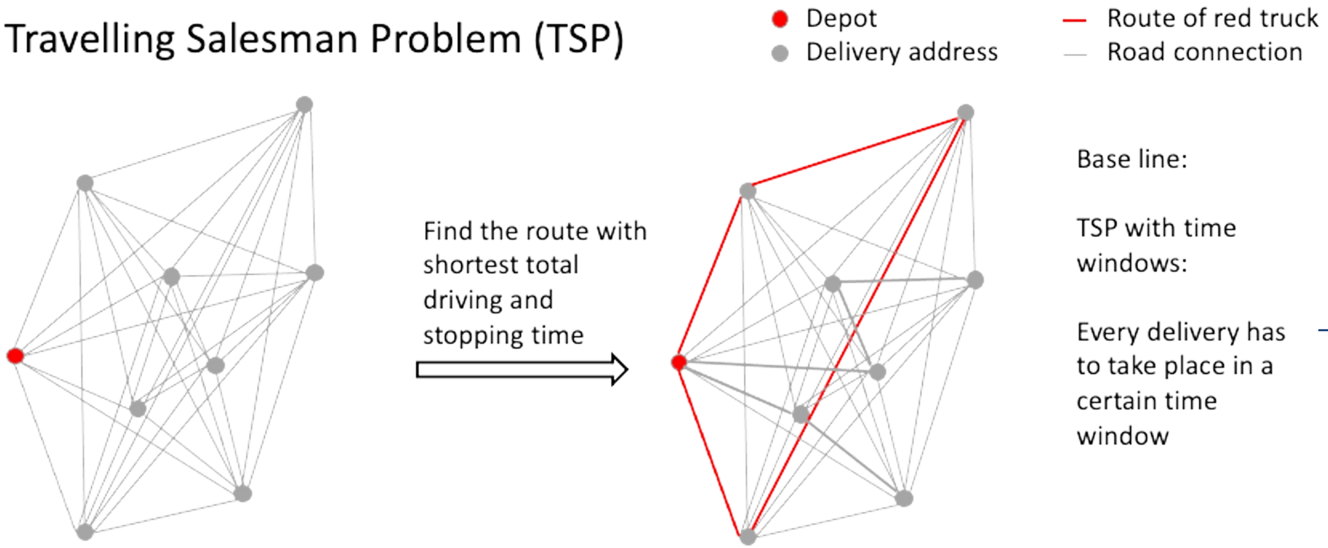


TSP with time windows

Tristan

I-NUF

INPUTS
- List of orders with delivery addresses and time windows
- Travel time matrix



Base line:

TSP with time windows:

Every delivery has to take place in a certain time window

OUTPUTS
- Optimized route / manifest

INPUTS
Stop data
Delivery data

→ 1. Cruising time prediction → 2. Route optimization → 3. Route Simulation →

OUTPUTS
Route time
Driving time/dist
Cruising delays

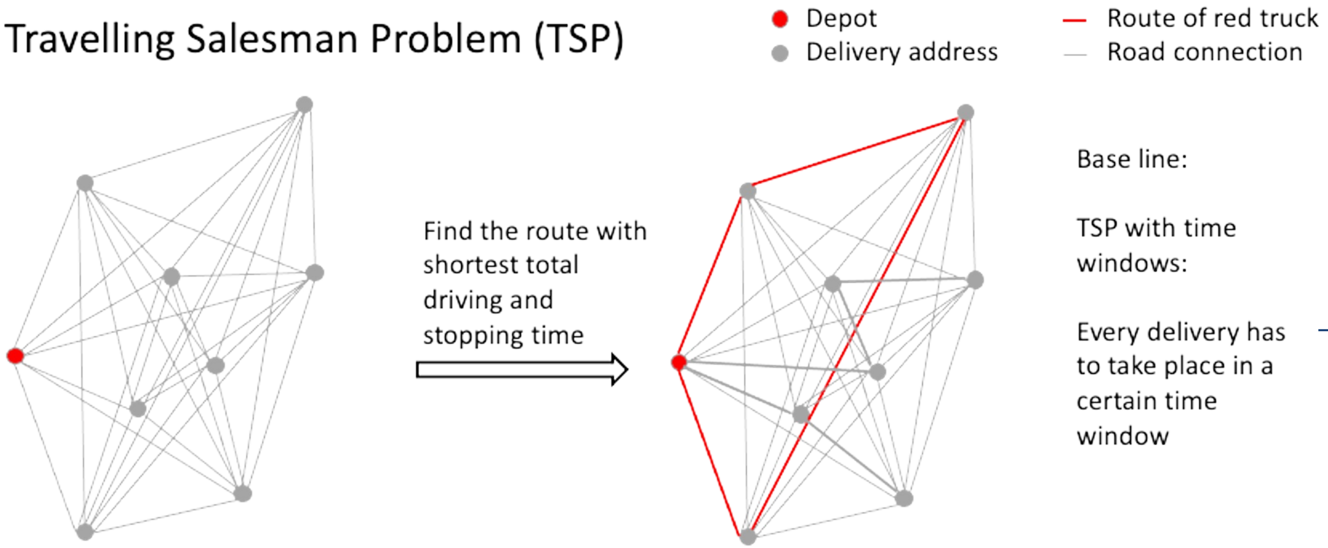
Tristan

I-NUF

Time dependent TSP with time windows (TD-TSP TW)

In addition: Considers different travel times during different hours of the day

INPUTS
- List of orders with delivery addresses and time windows
- **Time dependent travel time matrix**



Base line:

TSP with time windows:

Every delivery has to take place in a certain time window

OUTPUTS
- Optimized route / manifest

INPUTS Stop data Delivery data	→	1. Cruising time prediction	→	2. Route optimization	→	3. Route Simulation	→	**OUTPUTS** Route time Driving time/dist Cruising delays

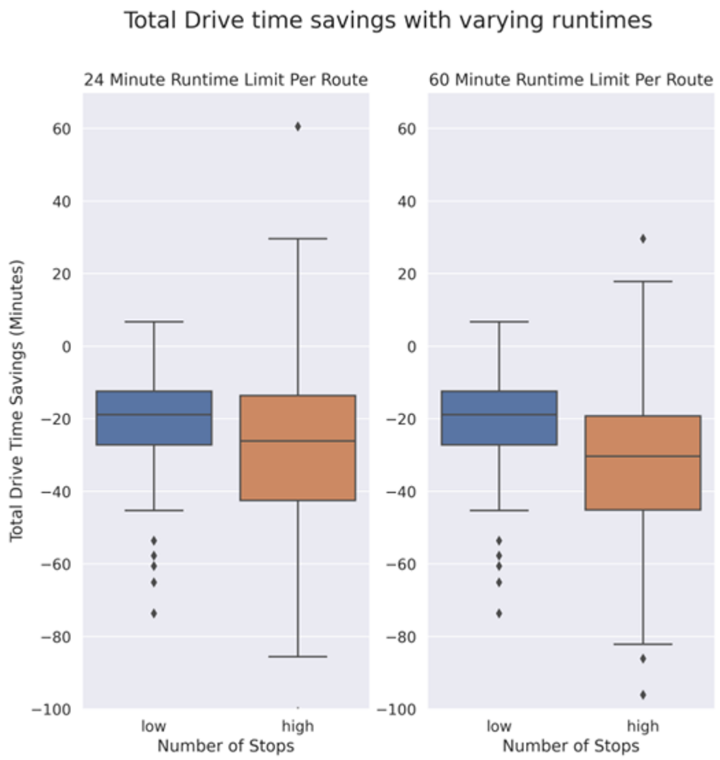
Tristan

Varying Number of Stops

Observation: Lower number of Stops lead to better average savings per stop

Takeaways:

- Total drive time savings are still larger under the high stop scenarios. Standardization creates an inverse relationship.
- Increased complexity from tripling number of stops requires significant runtime increase to reach optimal values in BRKGA



INPUTS
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Delivery data

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OUTPUTS
Route time
Driving time/dist
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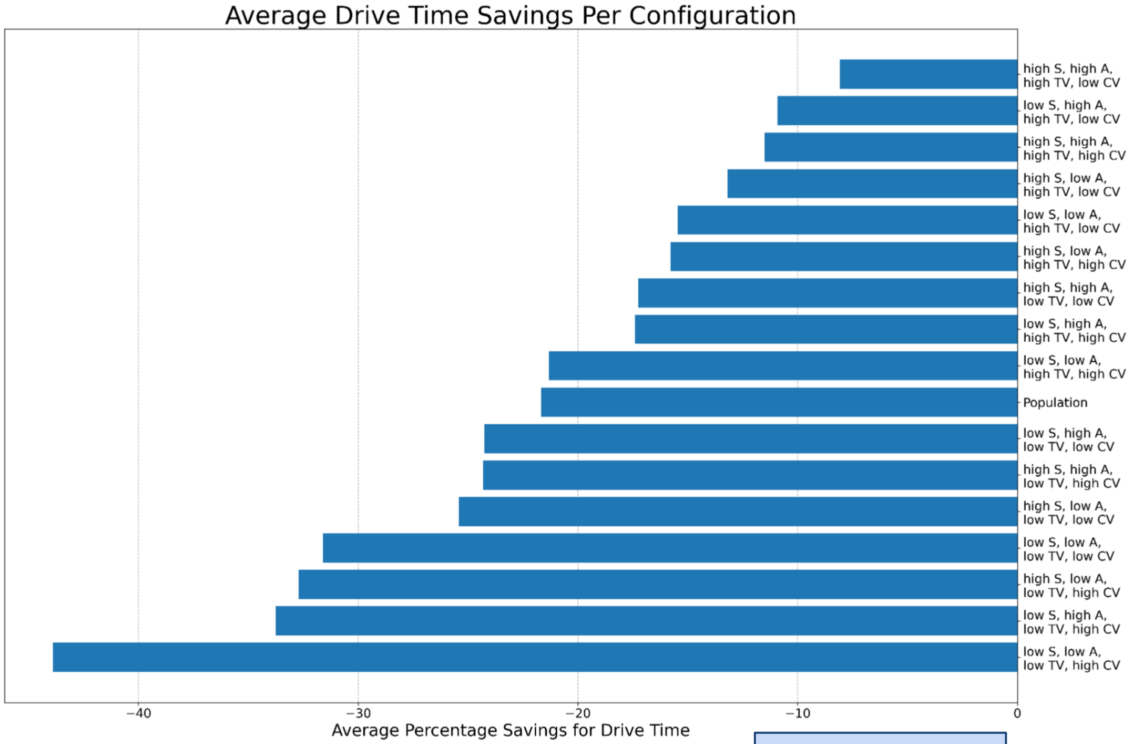
Drive Time Savings

Best performing Config:
Low Stops, **Low** Area, **Low** Travel distance variance, **High** Cruise time variance

Average Percent Savings: 43%

Every configuration with a **low** travel matrix variance and a **high** cruise time variance was above the population average

Acronyms:
S – Stops, **A** – Area
TV – Travel matrix Variance
CV – Cruise time Variance



INPUTS
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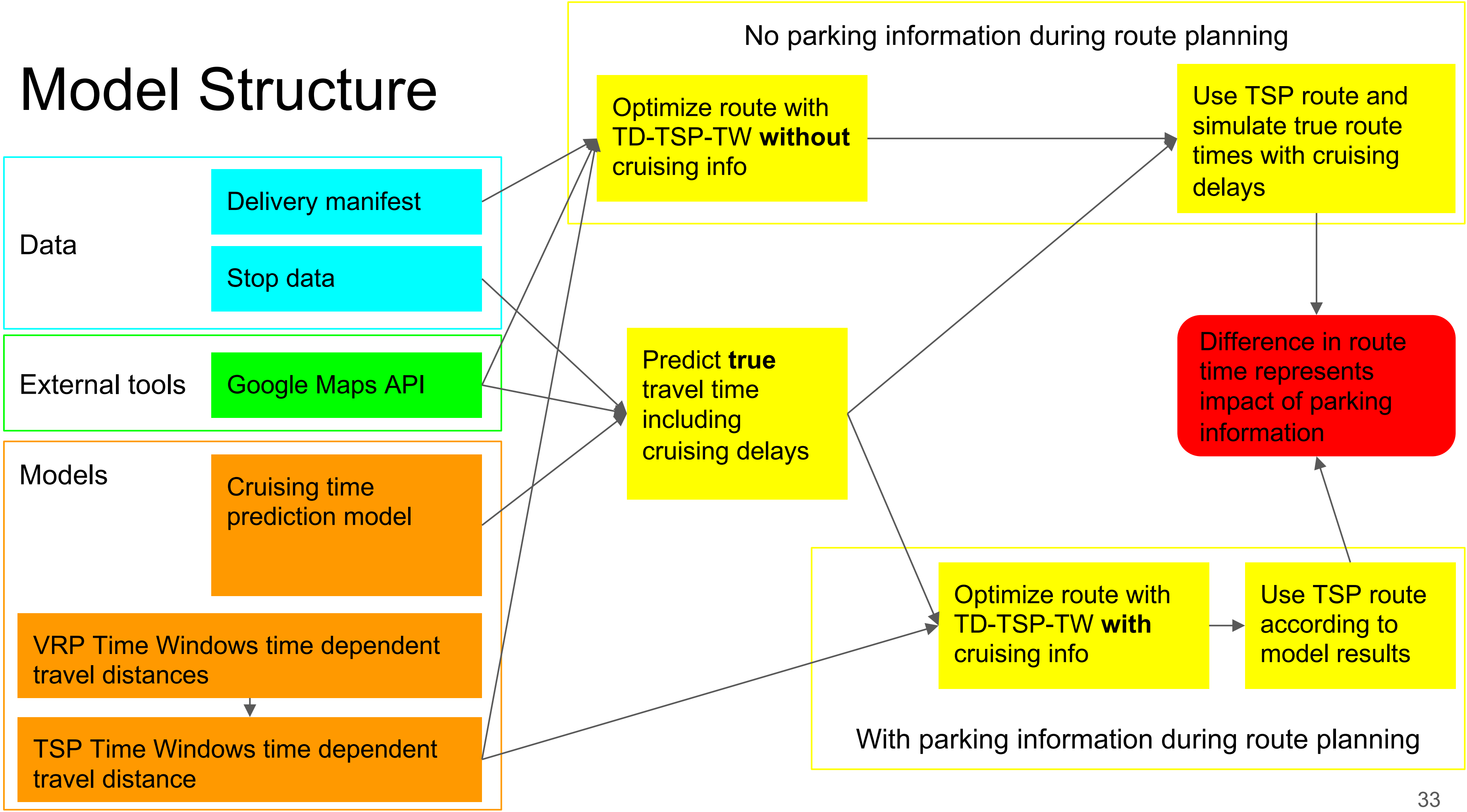
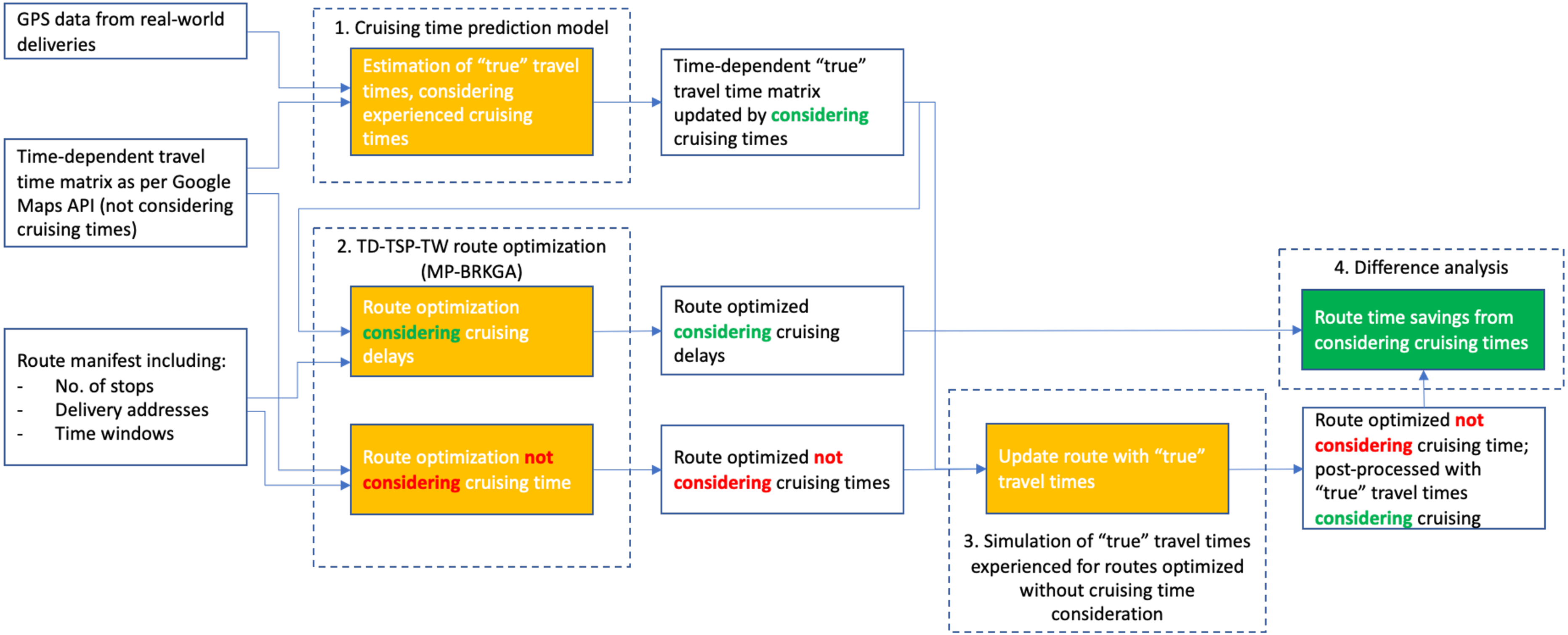
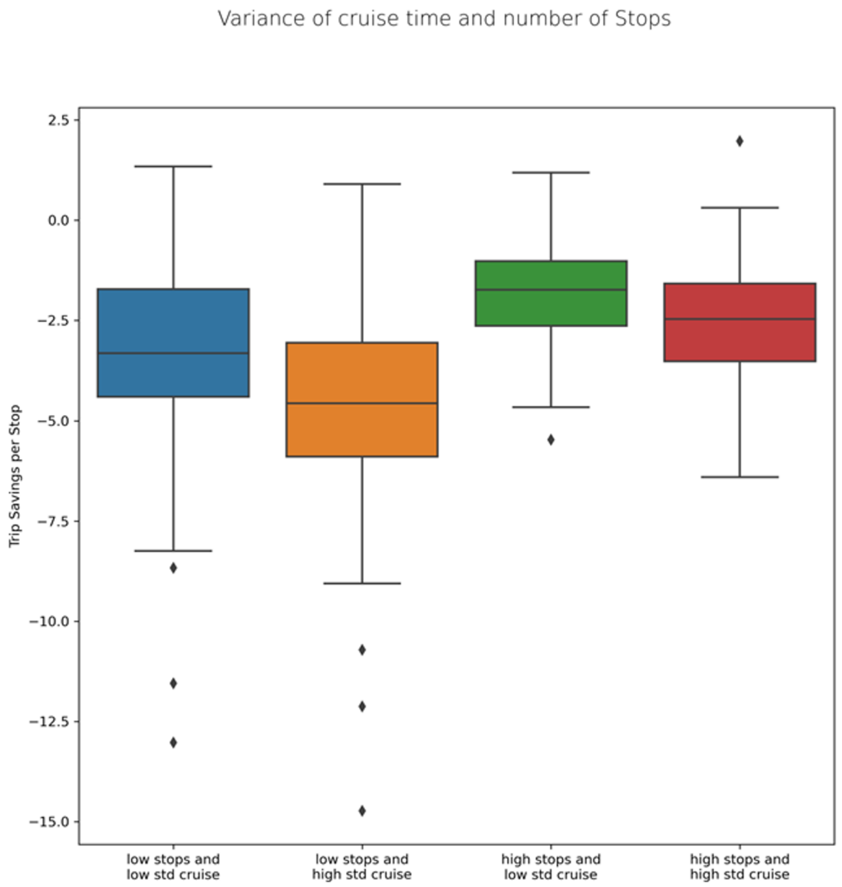
Model Structure



Detailed Simulation Structure



Interaction Effect



ANOVA Results

	Sum of Squares	df	F-value	p-value
Intercept	4,364.374	1.0	853.244	1.248e-100
Area	25.282	1.0	4.943	2.677e-02
No. of stops	263.744	1.0	51.562	3.483e-12
SD cruising time	70.337	1.0	13.751	2.386e-04
SD travel time matrix	18.553	1.0	3.627	5.757e-02
No. of stops : SD travel time matrix	92.117	1.0	18.009	2.744e-05
Residual	2,015.325	394.0		

Synthetic Study - Findings

- Variance of cruise time delays, the number of stops, and shape of the route all play a significant role in how impactful route savings are when cruising delays are considered in route generation.
- Average drive time savings of 21.6% with savings up to 60% for some routes.
- **Few** Stops, **Homogeneous** Shape, **High** Cruising delay variance have largest mean drive time savings of 39% and an average of -5.18 minutes per stop.