Enhancing Last-Mile Delivery Planning: Understanding Drivers' Preferences with Machine Learning

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Problem Statement

- **Inefficient Routing Choices:**
  - Drivers often select routes based on personal preferences.
  - Tendency to choose familiar roads over shorter, more efficient paths.
- **Impact on Last-Mile Delivery:**
  - Can lead to increased travel time and operational costs.
  - Potential for reduced customer satisfaction due to delayed deliveries.
- **Lack of Data Utilization:**
  - Existing systems do not adequately learn from and adapt to individual drivers' preferences.
  - The need for a data-driven approach to optimize routes according to both efficiency and driver preference.

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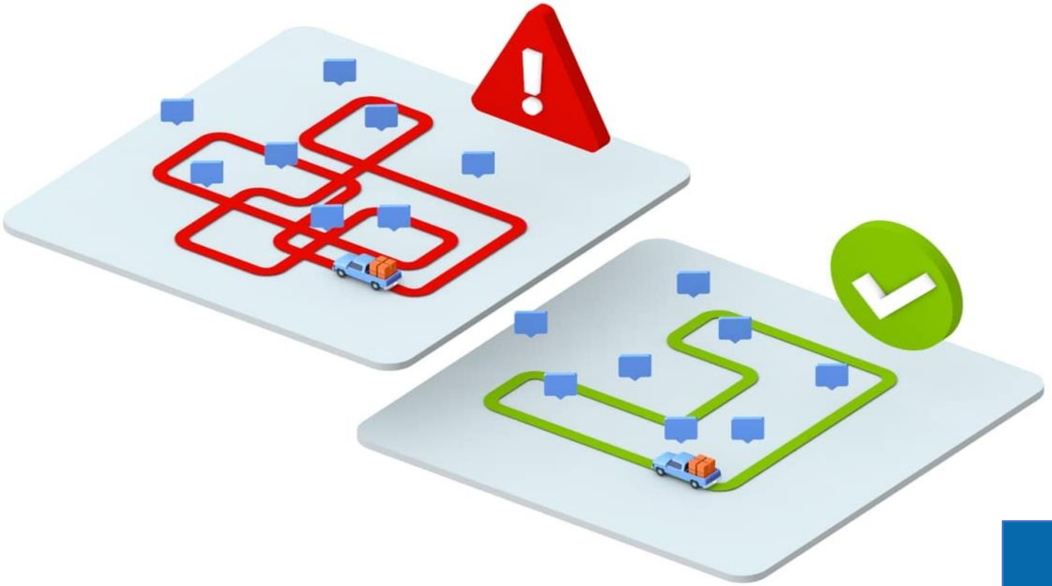
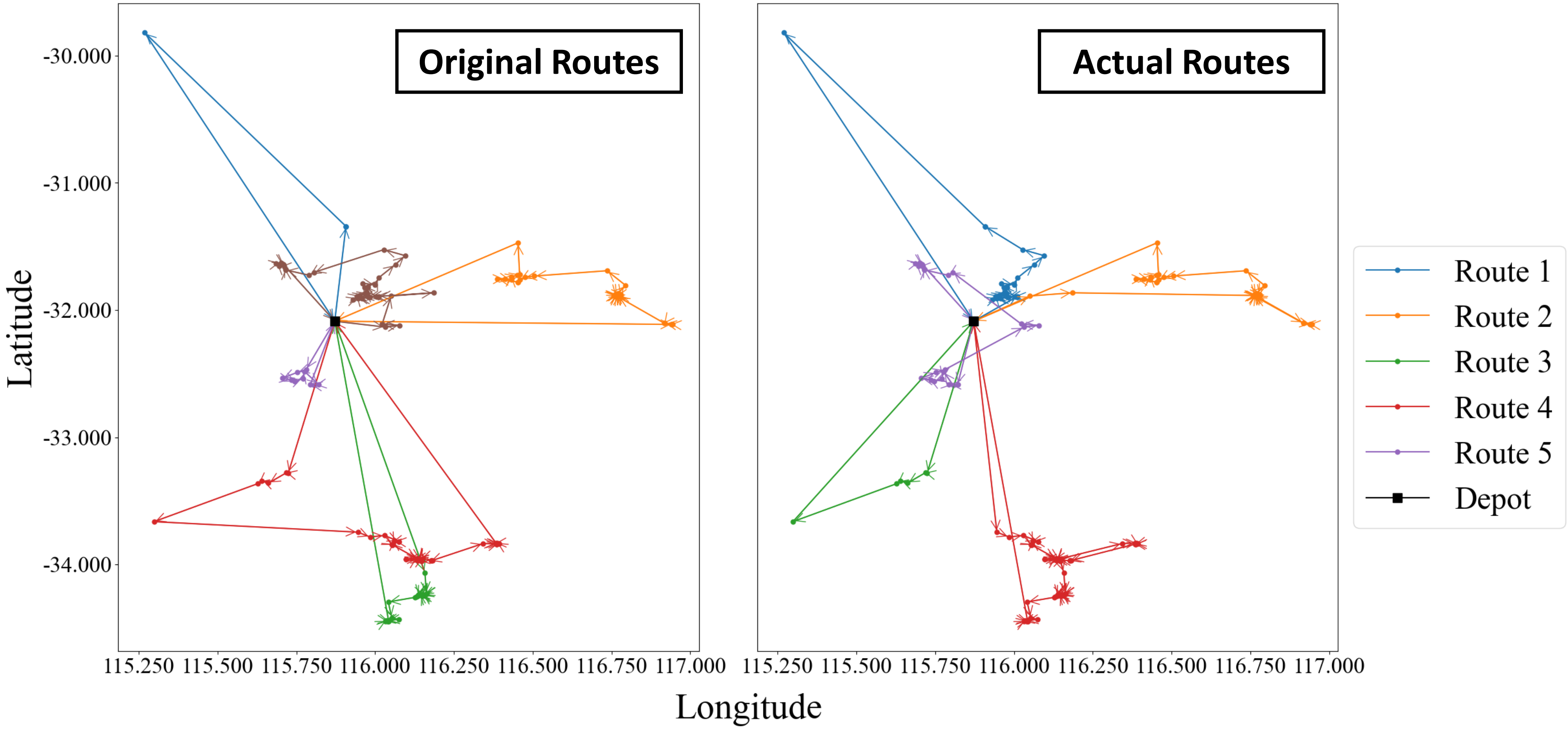
Research Objectives

- **Adaptive Learning Approach:**
  - Adapt and learn from historical data to align with both drivers' and route planners' preferences.
- **Humanized & Intelligent Delivery Process:**
  - Infuse the routing selection process with data-driven intelligence while respecting the drivers' preferences.
  - Enhance customer satisfaction by optimizing the efficiency and effectiveness of last-mile delivery.
- **Validation & Impact Assessment:**
  - Validate the proposed model with real-world data to evaluate its effectiveness.
  - Measure the improvement in routing solutions, balancing efficiency with drivers' and planners' preferences.

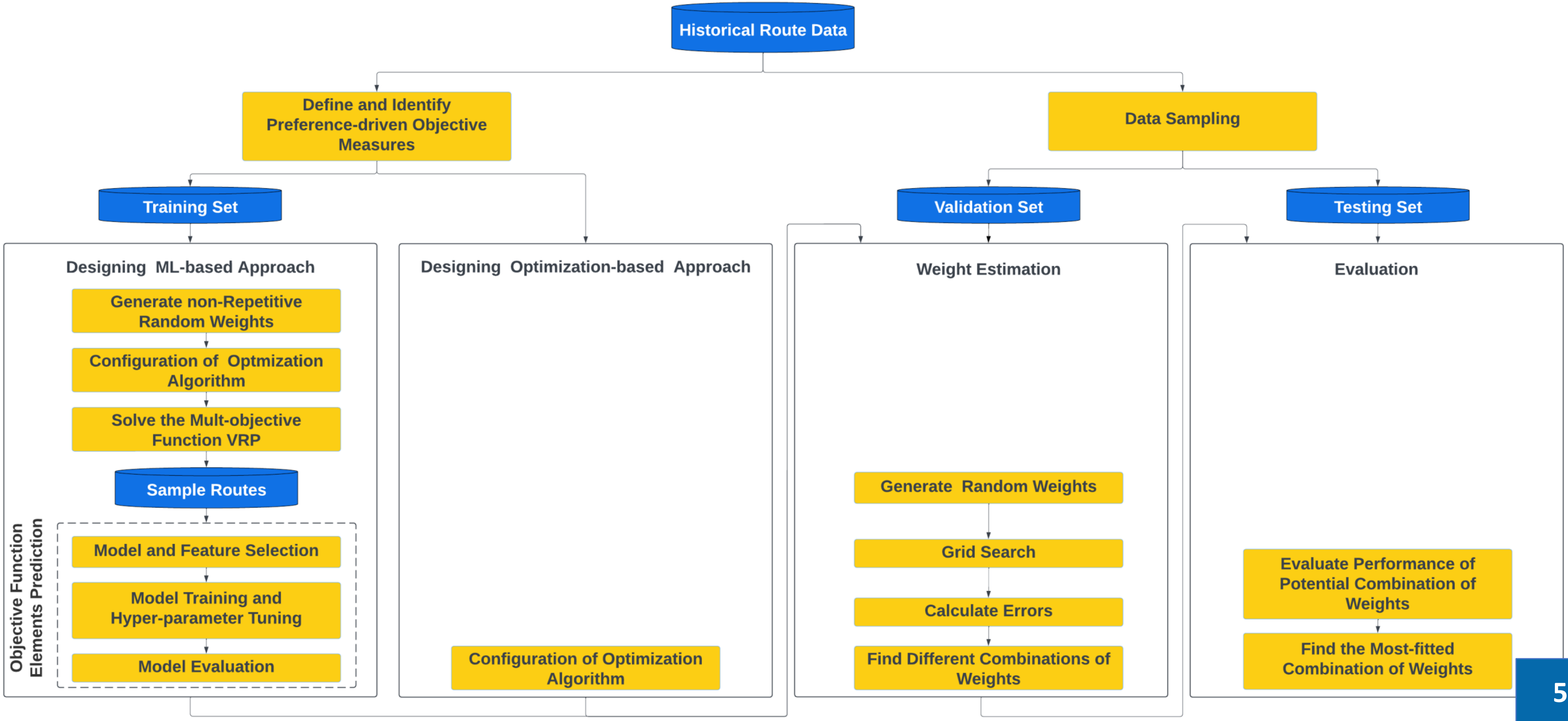


How does the final routes (actual routes) deviate from commercial routing algorithm's recommended routes (original routes)?



Research Methodology

Can we design a preference-based research framework?



Research Methodology

What are the components of the objective function based on historical data?

Measure	Mode		Mean		Median	
	Original	*Actual*	*Original*	*Actual*	*Original*	*Actual*
Number of vehicles	3	2	9.4	9.2	5	5
Average distance per route (km)	60.9	60.9	1488.5	1447.4	848.1	794.9
Route balance (number of customers)	0	0	30.6	22.9	33	12
Route balance (travel time)	13.9	13.9	106.3	107.3	65.5	62.4
Route balance (travel distance)	16	16	80.3	79.9	56	56
Route Compactness	9.9	9.9	10.5	11.9	7.9	8.8
Route overlap	0	0	411.1	398.3	50	46

Objective function

$$\text{Min } W_1 \times Distance + W_2 \times Number\ of\ Vehicles + W_3 \times Balance$$

Research Methodology

What is the best combination of weight?

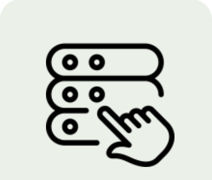
Applying a grid-search methodology (Optimization-based grid search)

Random different combination of weights

Run the meta-heuristic for each combination of weight

(the meta-heuristic in our case is ALNS)

Evaluate the results for each combination of weight based on the clients' final routes



Select the most appropriate combination of weight

Challenges

Run time!

Research Methodology

What is the best combination of weight?

Applying a grid-search methodology using Predictive models (ML-based grid-search)

Make a dataset using random combination of weights and ALNS

→

Random different combination of weights

→

Predict the objective function terms using Random Forest

→

Evaluate the results for each combination of weight based on the clients' final routes

→

Select the most appropriate combination of weight

Results

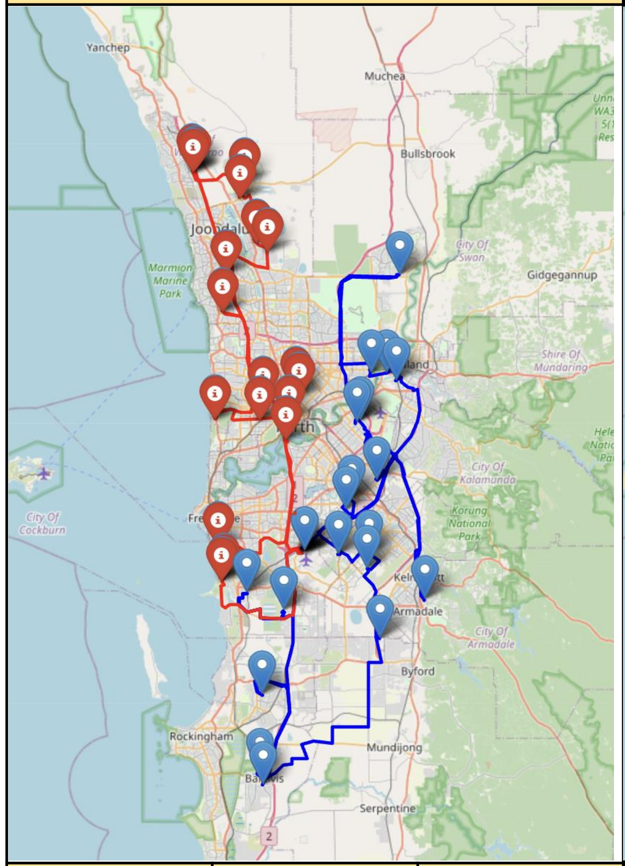
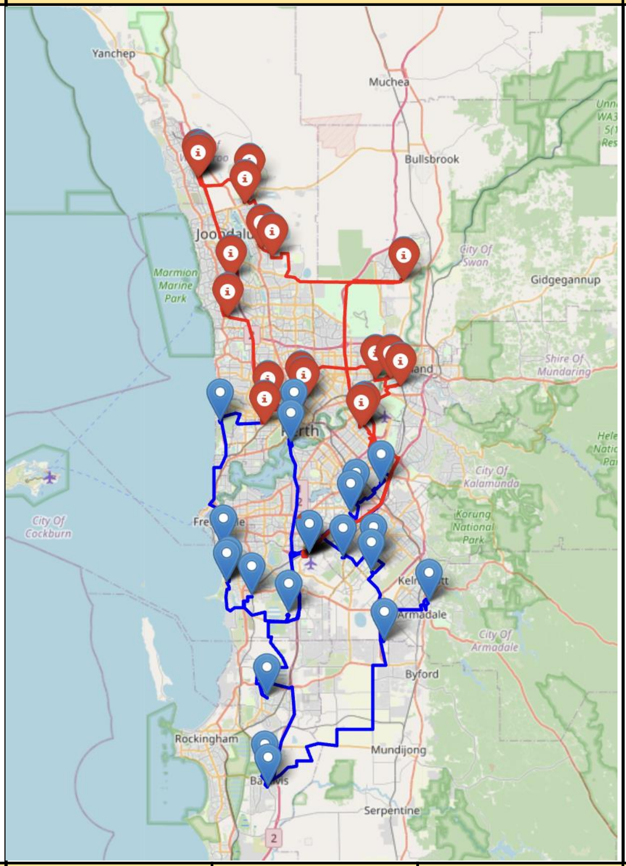
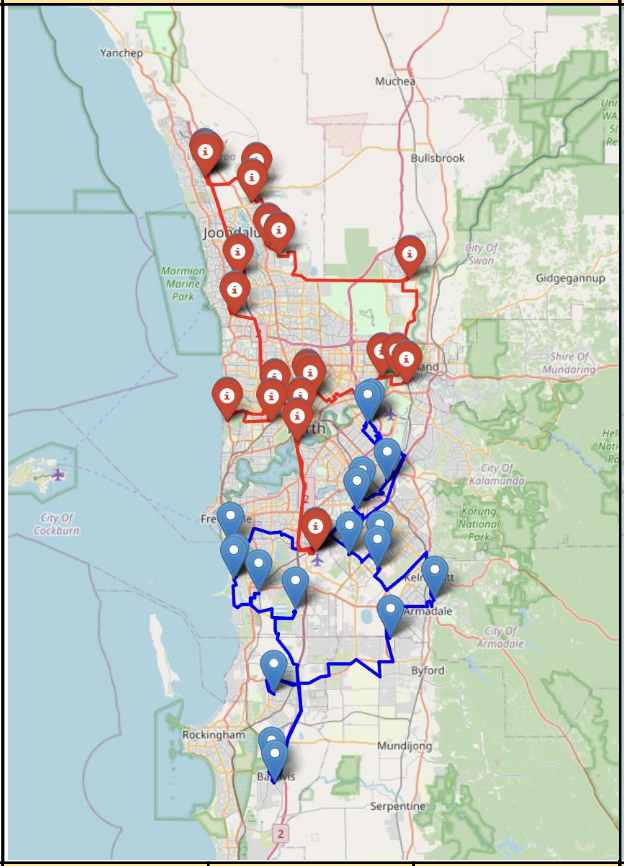
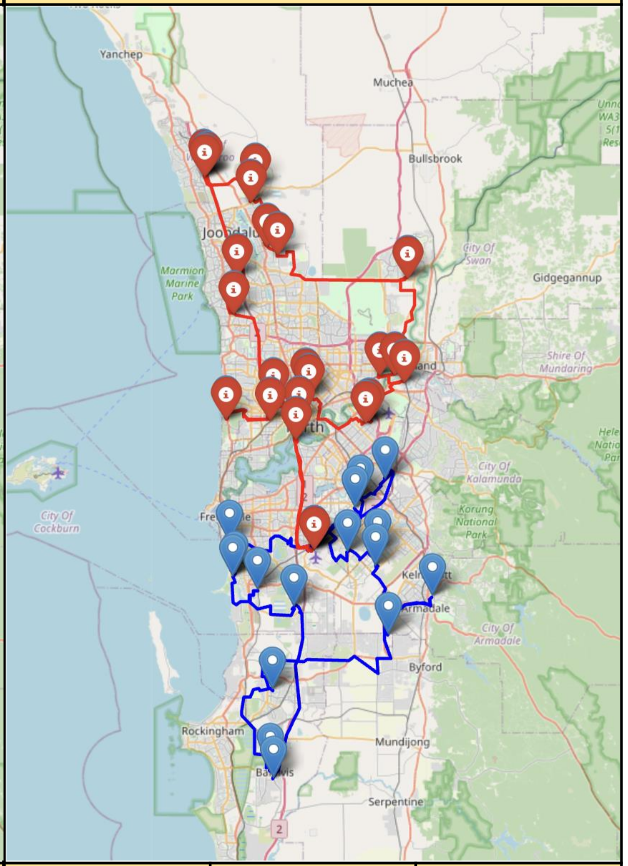
The weights recommended by Optimization-based and ML-based grid search

Runtime (Hour)	Best-found Combination of Weights		
	W_1	W_2	W_3
Optimization-based Weight Estimation			
61.515	0.842	0.153	0.005
ML-based Weight Estimation			
43.923	0.847	0.151	0.002

The finding is Robust

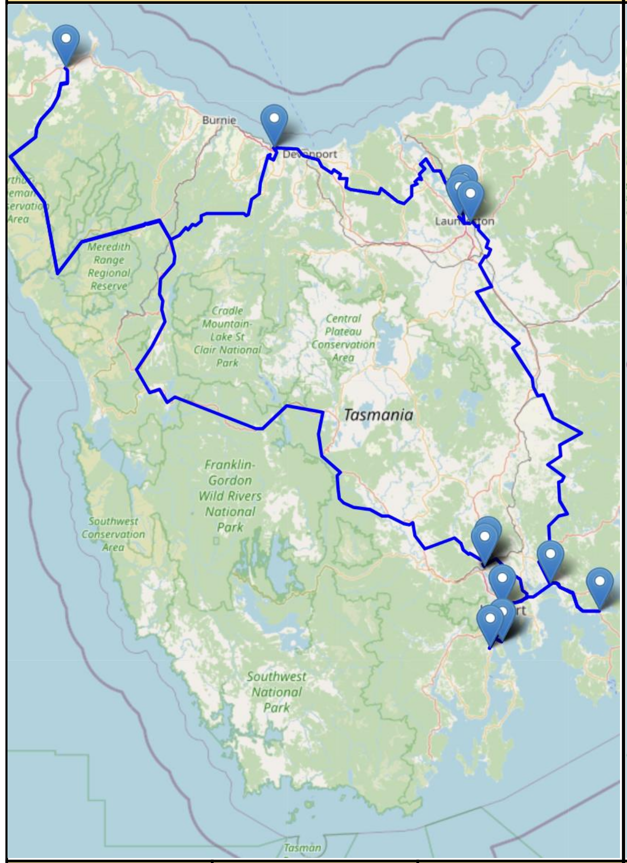
But! Which one should be chosen?

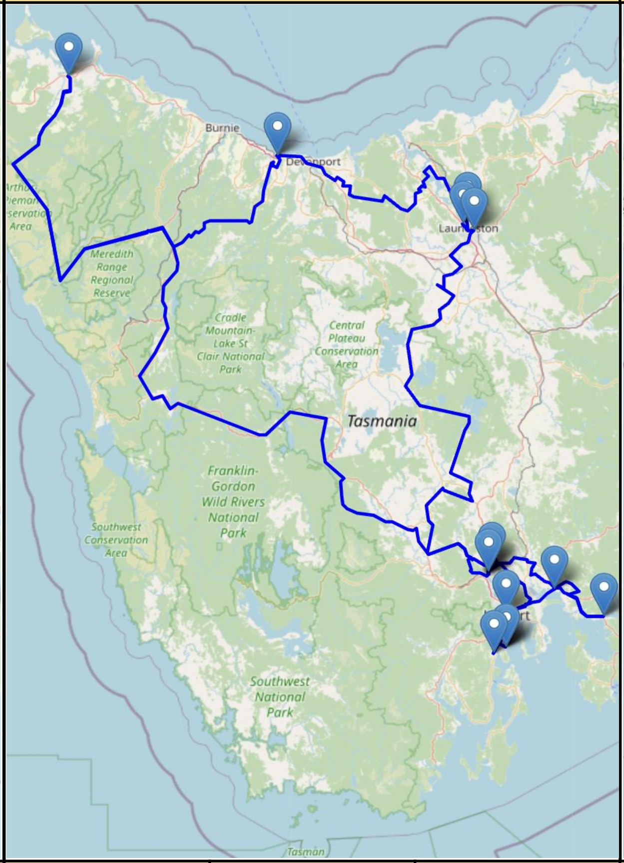
Sample 1: Compare some results of ML-based weight estimation approach with Original and Sync

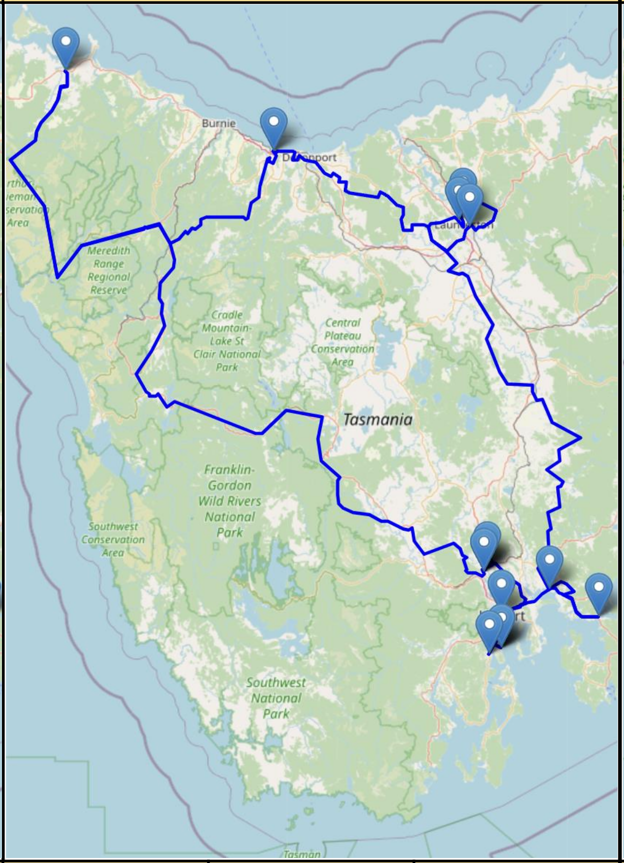
ML-based weighted MOP Output			OP-based weighted MOP Output			Sync Output			Original Output		
											
# Vehicle	Distance	Balance	# Vehicle	Distance	Balance	# Vehicle	Distance	Balance	# Vehicle	Distance	Balance
2	411.580	0	2	416.520	0	2	420.805	2	2	403.693	6

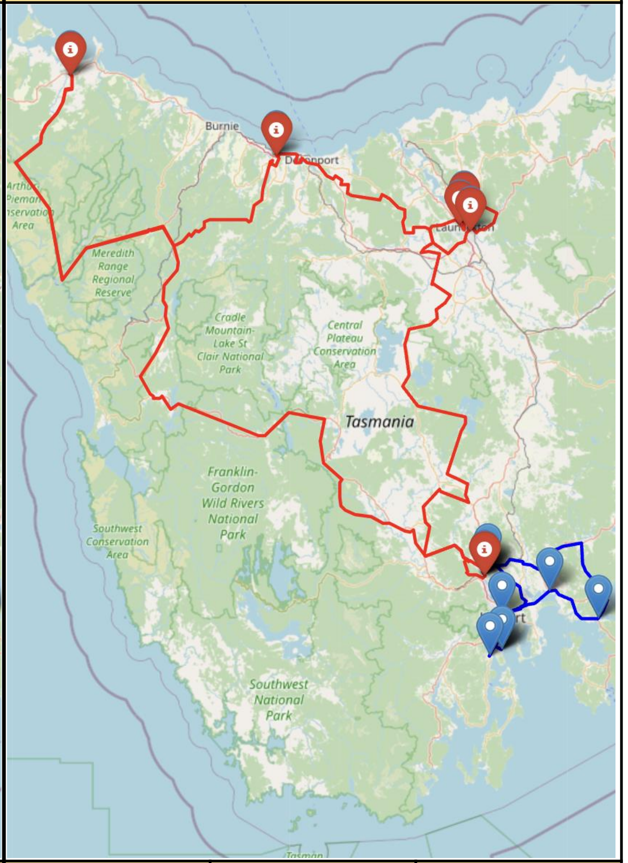
Results

Sample 2: Compare some results of ML-based weight estimation approach with Original and Sync









ML-based weighted MOP Output			OP-based weighted MOP Output			Sync Output			Original Output		
# Vehicle	Distance	Balance	# Vehicle	Distance	Balance	# Vehicle	Distance	Balance	# Vehicle	Distance	Balance
1	1401.628	0	1	1417.735	0	1	1488.951	0	2	1588.120	2

Conclusion

- ✓ The study introduced a **preference learning** approach to enhance last-mile delivery logistics, considering drivers' and service providers' route preferences.
- ✓ ALNS was efficient in exploring potential **routing solutions**, while sampling techniques identified recommended routes **systematically**.
- ✓ ML models integrated into the sampling process enhanced efficiency and were evaluated against ALNS in terms of **run-time** and **solution quality.**
- ✓ By utilizing actual historical routing data, the study facilitated learning and adaptation to the **preferences of both drivers** and **route planners**, introducing a human element to the vehicle routing problem (VRP).
- ✓ The study showcased a comprehensive **case analysis** using real data from a commercial last-mile routing optimization platform.
- ✓ The approach supports more informed, human-centered decision-making in logistics optimization by accounting for **personal preferences** and other **non-distance factors** in route selection.

Thank You!

Any Question?